CONDITION RATING MODELS FOR UNDERGROUND INFRASTRUCTURE: SUSTAINABLE WATER MAINS

by

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ABSTRACT

CONDITION RATING MODELS FOR UNDERGROUND INFRASTRUCTURE: SUSTAINABLE WATER MAINS

Hassan A. Al Barqawi

The Canadian Water and Wastewater Association (CWWA), in a study to assess the status of municipal water distribution system, reported that $12.5 billion would have to be invested over 15-year (1997 - 2012) period to replace the existing deteriorated water mains and construct new mains to cope with the projected population growth. Consequently, Canadian municipalities face a great challenge of managing these replacement and new installation projects efficiently. One of these challenges is how to assess the condition rating of buried water mains. This is because water mains are typically underground, operated under pressure, and usually inaccessible. Condition rating is a mandatory process to establish and employ management strategies for an asset. To assess the condition of water mains, current research considers physical, environmental, and operational factors and their effect on different types of mains (i.e. Cast Iron, Ductile Iron, and Asbestos). A condition rating scale and its associated rehabilitation actions are proposed. This scale is divided into 6 categories, which numerically range from "0" to "10" and linguistically from "critical" to "Excellent".

Condition rating models are developed to assess and set up rehabilitation priority for water mains using two different approaches; (i) artificial neural network (ANN) and (ii) analytical hierarchy process (AHP). However, a comprehensive integrated AHP/ANN model is developed considering more factors in order to increase the accuracy and

efficiency of the developed framework and model. Based on the developed AHP/ANN model, deterioration curves are generated for cast and ductile iron water mains.

Finally, an automated, user-friendly, web-based condition rating tool (CR-Predictor) is developed, based on the AHP and ANN approaches, to assess condition rating. It is coded in (ASP.Net) language. A case example has been worked out to demonstrate the usage and capabilities of the developed system.

The developed tool and models are relevant to researchers and practitioners (municipal engineers, consultants, and contractors) in order to prioritize pipe inspection and rehabilitation planning for existing water mains.

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NOMENCLATURE & ABBREVIATIONS

AEij	Attributes Effect Value of sub-factor j within the factor i,
AC	Asbestos Cement pipes
AEM	Acoustic Emission Monitoring
AET	Acoustic Emission Testing
AHP	Analytical Hierarchy Process
ANN	Artificial Neural Network
AIP	Average Invalidity Percent
AVP	Average Validity Percent
BR	Breakage Rate
BPNN	Back Propagation Neural Network
Ci	Actual Value
CCTV	In-line Closed Circuit Television
CI	Cast Iron pipes
C.I	Consistency Index
CPP	Concrete Pressure pipes
CR	Condition Rating
C.R	Consistency Ratio
CR-Predictor	Condition Rating Predictor
DI	Ductile Iron pipes
Ei	Estimated / Predicted Value
GPR	Ground Penetrating Radar
GRP	Glass-Fiber Reinforced Plastic pipes
HDPE	High Density Polyethylene pipes
IE	Impact Echo
LDPE	Low Density Polyethylene pipes
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MDPE	Medium Density Polyethylene pipes

MFL	Magnetic Flux Leakage
NDT	Non-destructive Technique
PCCP	Pre-stressed Concrete Cylinder pipes
PVC	Polyvinyl Chloride pipes
PE	Polyethylene pipes
r	Correlation Coefficient
RFEC/TC	Remote Field Eddy Current/ Transmission Coupling
R.I	Ratio of the average consistency index
RMSE	Root Mean Squared Error
SASW	Spectral Analysis of Surface Waves
$SDWij$	Overall Sub-factor Decomposed Weight
UPVC	Un-plasticized Polyvinyl Chloride pipes
Vij	Weight of sub-factor j within the factor i
W.S	Welding Steel pipes
Wi	Weight of factor i
λmax	The maximum eigenvalue of the comparison matrix

CHAPTER I

INTRODUCTION

I.1. OVERVIEW

Water distribution systems consist of different types of buried pipes (i.e Cast Iron, Ductile Iron, Asbestos Cement, and Polyvinyl Chloride). As water distribution system continues to age, the structural condition become worse and hydraulic capacity as well as performance decrease. Deterioration of water mains is neither uniform nor identical. It varies based on different physical, environmental, and operational factors, which cause variations in water main conditions. Therefore, it is crucial to inspect and assess water system condition in order to effectively maintain and upgrade its elements, which will save a lot of time and money. It is reported in the United States that the cost of replacing all water mains would run to US $348 billion, while upgrading would cost only US $77 billion over the next 20 years (Baer, 1998). In addition, it is reported, in the ASCE infrastructure report card, that the overall grade of water mains condition is "D-" where there is a shortage of $11 billion/year for upgrading the water system (ASCE, 2005).

The Canadian Water and Wastewater Association (CWWA) reported, in 1997, that the cost of replacing more than 112,000 kilometers of water mains in Canada would run to $34 billion (Best Practices, 2003b). Allouche et al., (2002) reported that municipalities estimated the need of one billion dollars in order to repair damages caused by water main leakages. These figures show the enormity of water main deterioration problem in the United States and Canada. Therefore, knowing current condition of water mains is essential to municipal engineers because it assists them to predict their performance and to optimize their replacement, maintenance, or rehabilitation activities.

I.2. PROBLEM STATEMENT AND RESEARCH OBJECTIVES

Water distribution systems consist of hundreds and even thousands of different types of buried pipelines, which are installed at different ages. The conditions of these pipes are uncertain and interrelated with different time-dependent factors. Subsequently, engineers and decision makers are often challenged of how to plan replacement or rehabilitation activities for existing water mains and on which bases.

The condition of water mains can be determined using two methods: (1) applying direct inspection methods for the whole pipes in the network, which is often too expensive and time consuming, or (2) using one of the developed condition rating models, which is considered an effective and inexpensive alternative. However, a previous study, involved 45 water utilities from North America and UK, has shown that only 30% of water utilities applied models from literature to assist them in planning water mains renewal. This low rate indicates that research efforts are often not interpreted into operational tools (Kliener et al., 2002).

In addition, no standard condition rating system (rating scale and its associated rehabilitation actions) for water mains is developed in the United States and Canada until today. Only approximations and expert opinions are used to determine the condition, expected life, and rehabilitation actions for water mains.

Therefore, the objective of current research is to provide underground infrastructure professionals with effective and practical models in order to assess the condition of existing buried water mains. Current research also develops a condition rating scale with its associated course of actions. The developed models in addition to the condition rating scale are employed as a pre-investigation tool that assesses the condition of water mains before further investigation is warranted.

The objectives of this research can be summarized as follows:

- Design a condition rating scale for water mains.
- Develop a condition rating model to assess the condition of existing buried water pipes.
- Build deterioration curves for water mains.
- Develop a prototype web-based automated tool, which provides condition rating values, in order to assist municipal personnel to plan water main projects.

I.3. RESEARCH METHODOLOGY

Current research aims developing condition rating model and tool to assess municipal engineers in order to prioritize and plan water system rehabilitation actions. Therefore, in order to meet the aforementioned objectives, the following procedure is carried out:

I.3.1. Literature Review

A comprehensive literature review is carried out in different areas using different sources including books, journals, and the Internet. The literature includes type and failure of pipes, factors contributing to water mains deterioration, techniques used to inspect and assess existing water mains, condition rating and deterioration models. In addition, artificial neural network (ANN) and analytical hierarchy process (AHP) techniques are represented.

I.3.2. Data Collection

Historical data are collected from three municipalities: Moncton, NB; London, ON; and Longueiul, QC. A questionnaire is designed and forwarded to fifty municipal engineers and experts in Canada and the United States. It collects data related to a standard condition rating scale, pair-wise comparison matrices among main factors and their sub-factors.

I.3.3. Development of Condition Rating Scale and Models

The development passes through the following five phases:

1. Design a condition rating scale.
2. Develop a neural network (ANN) condition rating model.
3. Develop an analytical hierarchy process (AHP) condition rating model.
4. Design an integrated AHP/ANN model .
5. Design a proto-type web-based tool (CR-Predictor) based on the ANN and AHP approaches.

I.4. THESES ORGANIZATION

To accomplish the objectives of this research, literature search and synthesis on condition rating and deterioration models of water mains is done as shown in chapter II. Literature review covers type of pipes, factors that contribute to water main failure, and direct / indirect inspection techniques. Moreover, a detailed description of artificial neural network (ANN) and analytical hierarchy process (AHP) approaches and their application are reported. Therefore, the emphasis in literature and analysis focuses on these two approaches.

Chapter III provides an overview of the proposed research methodology including layout for building the ANN and AHP condition rating models. In addition, a prototype web-based condition rating tool (CR-Predictor) is presented.

Chapter IV presents the development of condition rating scale. It explains numerically and linguistically each category of the proposed scale along with its associated rehabilitation actions.

Chapter V describes the ANN framework that identifies input and output factors; explains model development; and presents the training and testing results. It also shows the model validation process. Discussion and analysis of results in addition to deterioration curves for different type of pipes are presented.

Chapter VI provides an overview of the AHP implementation framework, which describes the main contributing factors and sub-factors; AHP model development; and its application procedure. Discussion and analysis of results are presented

Chapter VII describes the development of a prototype web-based condition rating tool (CR-Predictor). Theoretical basis and configuration of the CR-Predictor schema for ANN and AHP approaches are presented. An application example of methodology implementation is shown in order to demonstrate the capabilities of the developed prediction condition rating tool. Finally, it presents discussion and analysis of results in addition to limitations of the CR-Predictor.

Chapter VIII presents conclusions, limitations of the developed models, and main research contributions, and recommendations for future research work.

CHAPTER II

LITERATURE REVIEW

II.1. OVERVIEW

This chapter consists of six sections as shown in Figure II-1. Section II-2 covers literature review of types and characteristics of pipes that are used in water networks: metallic, concrete, and poly pipes. This section also includes a review of pipe failure behavior based on their material.

Section II-3 illustrates different time-dependant factors that contribute to pipe deterioration. They include physical, environmental, and operational factors, which provide the basic terminology and framework of developing condition rating models.

Section II-4 presents an extensive literature review of the available direct techniques used to evaluate and inspect existing water lines. They include destructive and non- destructive techniques: visual, physical, ultrasonic spectrum, electromagnetic, and acoustic techniques. Then, it presents the indirect indicators and statistical methods used to analyze the four common types of problems that occur in water distribution systems. These include structural condition, hydraulic capacity, leakage, and water quality problems.

Section II-5 provides a literature review of existing condition rating and deterioration models used to predict pipe failure with different approaches.

The last two sections, section II-6 and section II-7, of this chapter presents an extensive literature review for artificial neural network (ANN) and analytical hierarchy process (AHP) approaches and its applications respectively. The literature review in those sections provides the criteria for subsequent developments of the models.

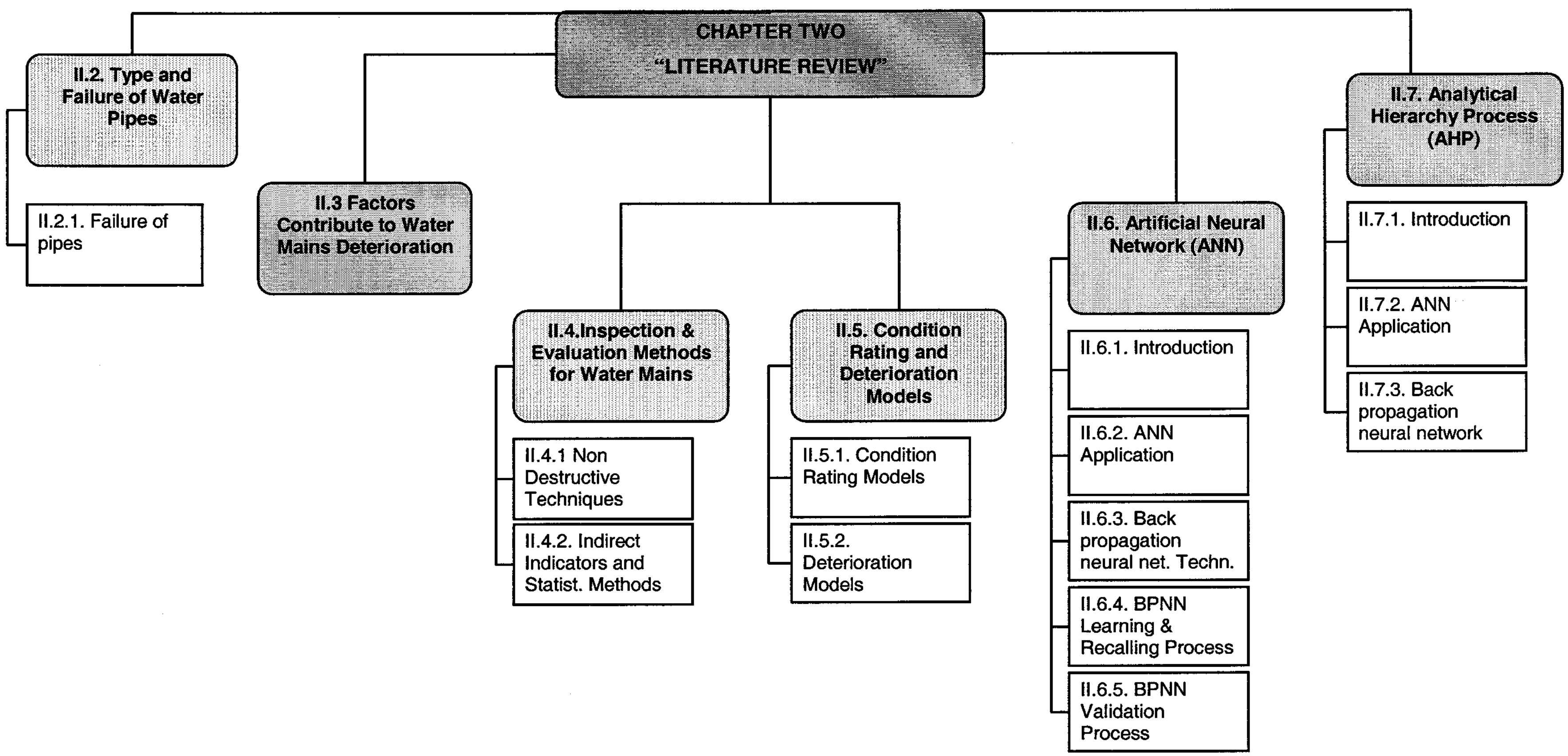

Figure II-1 Chapter 2 Content Diagram

II.2. TYPE AND FAILURE OF WATER PIPES

Water delivery system can be divided into two main categories: transmission and distribution lines. Transmission lines are the pipes that transfer water from main source to storage system (i.e. water tanks). They are considered the most expensive part in the system because of their higher initial construction costs (i.e. material, installation, equipments). Distribution lines are the pipes that carry water out from the storage system to the domestic users (i.e. residential buildings or industrial factories). The minimum diameter for a distribution pipe is two inches, and the minimum diameter required for serving fire hydrants is six inches.

Water mains consist of different types of pipes and materials. They are not only varying from country to country, but from a city to the other as well (Rajani and Kleiner, 2004). The major types of pipes that are commonly used in a water system are classified according to their material, as shown in Figure II-2. Each type of these pipes has its' own mechanical and thermal properties. It varies based on their material as shown in Table II-1 (Rajani et al., 2004).

Table II-1 Mechanical and Thermal Properties of pipes Material (Adapted from Rajani et al, 2004)

	Cast iron		Ductile iron	Asbestos cement	PVC	HDPE
	pit	spun				
Elastic modulus, GPa	120	137	165	20-25	2.25	0.69
Ultimate tensile strength, MPa	173	250	290	25	48	22
Strain to failure, %	0.5	0.5	7	1	10	10
Poisson's ratio	0.30	0.30	0.28	0.3	0.42	0.45
Thermal coefficient, $\times 10^{-6}/^{o}C$	12	12	11	8.5	79	220

It shows that strains to failure (%) of ductile iron and plastic pipes are significantly higher than those of cast iron and asbestos cement pipes. The thermal expansion coefficient of plastic pipes (P.V.C and P.E) is 7 and 20 times more than that of cast iron and ductile iron, respectively.

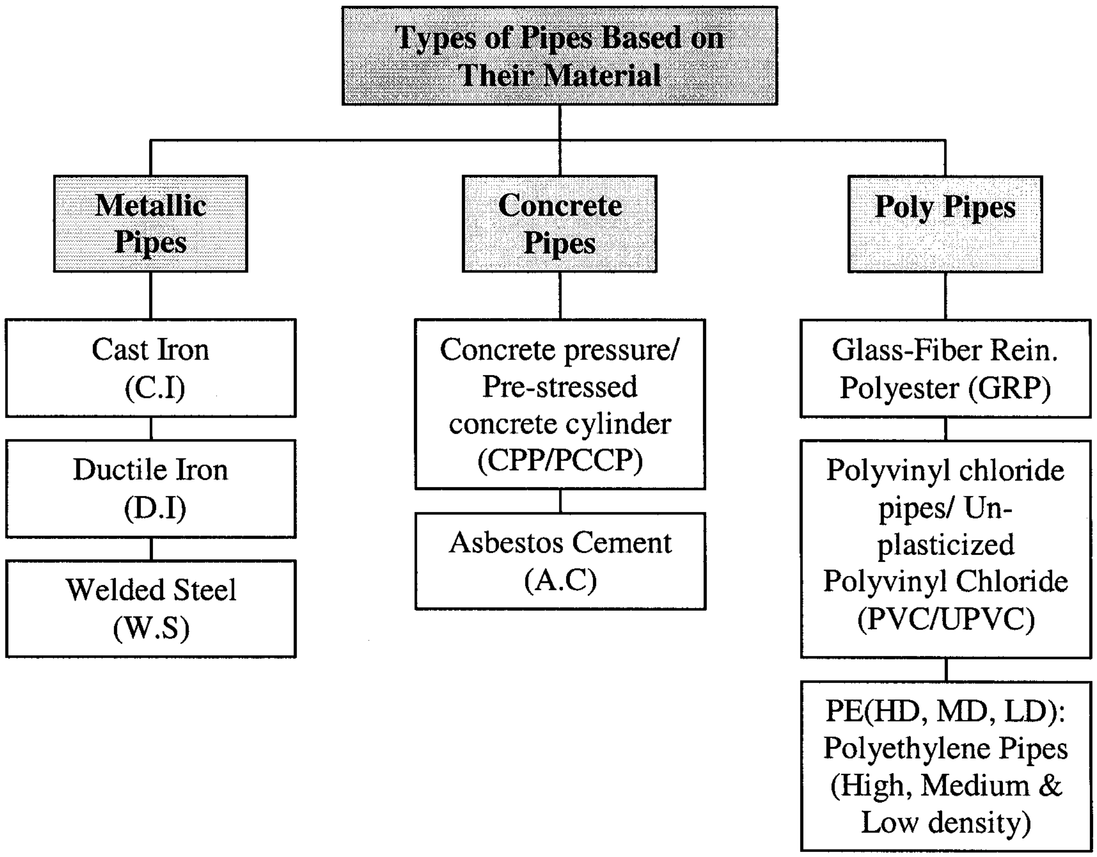

Figure II-2 Type of Water Pipes

Several factors should be considered in determining the most suitable and economical choice of pipe material. These factors include price, size, fittings availability, installation cost, location, ease of taping and repair, in addition to specific environmental conditions (i.e. operational pressure, soil type, water quality). Each type of these pipes has its own characteristics and advantages among others as shown in Appendix (A).

II.2.1. Failure of Water Mains Pipes

Pipes will deteriorate and fail overtime, but the rate of failure in pipes varies according to pipe's material and exposure to different environmental and operational conditions (Makar et al., 2000). Deterioration of pipes will affect the structural condition and hydraulic capacity of a water main, which decreases the system performance. Rajani and Kleiner, (2004) stated that deterioration of pipes generally could be classified into two categories: structural and internal deterioration. Structural deterioration affects the structural resiliency of pipes and their ability to resist various applied stresses. However, internal deterioration of pipes affects hydraulic capacity, water quality, and reduces the structural resiliency of the pipe.

Makar et al. (2000) stated that corrosion is the main reason of metallic pipes' failure. Metallic pipes deteriorate and corrode rapidly if they are laid in aggressive soil in which they might fail within a few years. Therefore, if metallic pipes are laid in aggressive soil, they should be wrapped in plastic sheets (Polyethylene encasement) to isolate the metal from soil, and hence, minimize the rate of pipe deterioration. However, the useful life of the polyethylene sheet is 30 years (Saint-Gobain, 2002).

Similarly, corrosion is the main reason of failure in Pre-stressed Concrete Pipes (CPP/PCCP). When enough number of the pre-stressed bars or wires are corroded and broken in a section of the pipe, concrete in that section will not carry out pressure. As a result, the pipe will rupture due to internal pressure (Makar et al., 2000). The CPP/PCCP are also weakened when they are laid in soil with low PH values resulting in lowering the

PH value of the cement mortar to a point where corrosion of the pre-stressing or reinforcing wires occurs (Rajani and Kleiner, 2004).

Asbestos Cements (AC) pipes can also be weakened and degraded when it is used to transfer aggressive water such as low PH and low alkalinity waters (Rajani and Kleiner, 2001). The degradation of pipe will release asbestos fibres, which are harmful to health, and mix it with the carried water through the water distribution system. In order to prevent this type of damage, the pipe should be lined with epoxy resin or cement mortar (FRS report, 1988).

Polyvinyl Chloride (PVC/uPVC) pipes have high resistance to deterioration and corrosion, and can be used in very corrosive environments, but they likely to be affected by deterioration if they are exposed to weather, chemical attack, or mechanical degradation from improper installation methods (Balga, 1973). The chemical attack resistance for PVC pipes usually decreases with the increase in concentration of a specific chemical. For example, organic chemicals such as solvents and gasoline will weaken PVC/uPVC pipes, resulting in failure of pipe by expansion and rupture. Similarly, the polyethylene pipes (PE) deteriorate and fail due to joint imperfections, material degradation, and improper pipe installation. In addition, organic chemicals can pass through the walls of the PE pipes (Blaga, 1981; Blaga, 1982; Best Practices, 2003b).

Based on the above discussion, deterioration of water mains varies due to certain surrounding and operational conditions. In order to decrease deterioration and failure of pipes, municipal engineers have to emanate comprehensive studies on physical, environmental, and operational conditions. Soil should also be tested before selecting pipe material. In other words, pipe material has to match surrounding conditions (i.e. soil, loading, temperature). They have to decide which type of pipe would be feasible to use under a proposed condition through sensitivity analysis and life cycle cost.

II.3. FACTORS THAT CONTRIBUTE TO WATER MAINS DETERIORATION

Various factors affect the breakage and deterioration rate of water mains. These factors include operational, environmental and physical characteristics (Kleiner et al., 2001). It also reported that breakage rate of buried pipes could be subjective due to time-dependent factors, climate conditions and soil type. Structural capacity of water main is subjected to external and internal loads, such as soil and operational pressure; traffic and frost loads; and third party interference (Rajani and Kleiner, 2001). Rajani and Kleiner (2002) classified water main deterioration factors into three types, as shown in Table II-2:

1. *Static factors*: they are static overtime due to properties of the pipe and installation practice. They include pipe material, diameter, wall thickness, soil (backfill) characteristics, and installation practices.
2. *Dynamic factors* (related to pipe surroundings and environment): they include age, soil properties, temperature of soil and water, moisture, electrical resistivity, bedding condition, and dynamic loadings.
3. *Operational factors*: they include replacement rate, protection methods such as cathodic protection, and water pressure.

Table II-2 Factors affecting pipe breakage rates (Rajani et al., 2002).

Static	Dynamic	Operational
material	age	replacement rates
diameter	temperatures (soil, water)	cathodic protection
wall thickness	soil moisture	water pressure
soil (backfill) characteristics	soil electrical resistivity	
installation	bedding condition	
	dynamic loadings	

Best Practices (2003b) classified the factors that contribute to water main deterioration into three groups. As shown in Table II-3:

1. *Physical factors*: pipe material, wall thickness, pipe age, diameter, type of joints, thrust restraint, pipe lining and coating, dissimilar metals, pipe vintage and manufacture processes.

2. *Environmental factors*: soil type, soil moisture, groundwater presence, climate, pipe location in the road, trench backfill materials, pipe bedding, underground disturbances, stray electrical currents, seismic activity, and installation practices.

3. *Operational factors*: internal water pressure, leakage, water quality, flow velocity, backflow potential, operational and maintenance practices.

Yan et al. (2003) consider in their developed condition rating model only physical and environmental factors. Physical factors consist of pipe age, pipe diameter, and pipe material. Environmental factors include road loading, soil condition, and surroundings. However, authors consider only one type of soil. Yan et al. (2003) recommended in their research the inclusion of other factors in future studies. Geem (2003) incorporated in the developed condition rating model seven physical and environmental factors including pipe material, bedding condition, corrosion, temperature, trench width, pipe diameter, and pipe age. Yet, the data used in developing this model were arbitrary generated. Najafi and Kulandaivel (2005) included seven physical and environmental factors in their developed model for predicting the condition of sewer pipes. These factors consist of pipe length, size, type of material, age, depth, slope, and type of sewer.

From above, deterioration of water system is neither uniform nor identical. it varies based on various uncertain factors, which cause variations in the condition.

Table II-3 Factors that Contribute to Water System Deterioration (Best Practices, 2003b)

Factor		Explanation
Physical	Pipe material	Pipes made from different materials fail in different ways.
	Pipe wall thickness	Corrosion will penetrate thinner walled pipe more quickly.
	Pipe age	Effects of pipe degradation become more apparent over time.
	Pipe vintage	Pipes made at a particular time and place may be more vulnerable to failure.
	Pipe diameter	Small diameter pipes are more susceptible to beam failure.
	Type of joints	Some types of joints have experienced premature failure (e.g., leadite joints).
	Thrust restraint	Inadequate restraint can increase longitudinal stresses.
	Pipe lining and coating	Lined and coated pipes are less susceptible to corrosion.
	Dissimilar metals	Dissimilar metals are susceptible to galvanic corrosion.
	Pipe installation	Poor installation practices can damage pipes, making them vulnerable to failure.
	Pipe manufacture	Defects in pipe walls produced by manufacturing errors can make pipes vulnerable to failure. This problem is most common in older pit cast pipes.
Environmental	Pipe bedding	Improper bedding may result in premature pipe failure.
	Trench backfill	Some backfill materials are corrosive or frost susceptible.
	Soil type	Some soils are corrosive; some soils experience significant volume changes in response to moisture changes, resulting in changes to pipe loading. Presence of hydrocarbons and solvents in soil may result in some pipe deterioration.
	Groundwater	Some groundwater is aggressive toward certain pipe materials.
	Climate	Climate influences frost penetration and soil moisture. Permafrost must be considered in the north.
	Pipe location	Migration of road salt into soil can increase the rate of corrosion.
	Disturbances	Underground disturbances in the immediate vicinity of an existing pipe can lead to actual damage or changes in the support and loading structure on the pipe.
	Stray electrical currents	Stray currents cause electrolytic corrosion.
	Seismic activity	Seismic activity can increase stresses on pipe and cause pressure surges.
Operational	Internal water pressure, transient pressure	Changes to internal water pressure will change stresses acting on the pipe.
	Leakage	Leakage erodes pipe bedding and increases soil moisture in the pipe zone.
	Water quality	Some water is aggressive, promoting corrosion
	Flow velocity	Rate of internal corrosion is greater in unlined dead-ended mains.
	Backflow potential	Cross connections with systems that do not contain potable water can contaminate water distribution system.
	O&M practices	Poor practices can compromise structural integrity and water quality.

II.4. INSPECTION AND EVALUATION METHODS FOR EXISTING WATER MAINS

Water mains inspection provides a vision of pipe condition based upon the identification of metal loss or defects. However, the output does not provide a complete assessment of current condition. Inspection of existing water mains is a very important process that can save time and money. MacLeod et al. (2000) stated that the cost of emergency repair of a pipeline could cost up to 50% more than that of similar repair under normal conditions. Therefore, if the critical sections of water system are identified and repaired before a catastrophic failure happen, the cost of emergency repairs can be significantly reduced (Allouche et al., 2002).

Best Practices (2003b) reported that inspecting the condition of water mains passes through two phases: (i) an initial assessment of structural condition, hydraulic capacity, leakage, and water quality based on the collected data and (ii) a more comprehensive investigation of identifiable problems based on the results of the first phase. Furthermore, Makar et al. (2000) reported that there are two main methods to evaluate the condition of water system. First method, *indirect indicators and statistical methods*, which are based on the collected data that show pipe damage, such as water audit and hydrostatic leakage test. Hence, statistical models can be developed to assess the condition of water system elements. Second method, *direct inspection and monitoring techniques*, applies destructive and non-destructive evaluation techniques (DT and NDT) that detects problems in individual pipes or at a particular point along the pipe. It provides a variety of information related to pipe conditions.

II.4.1. Non-Destructive Monitoring and Inspection Techniques

Based on the inspection scheme, previous studies divide the destructive and non-destructive methods, which assess the condition of water mains, into five categories as shown Figure II-3: acoustic, electromagnetic, ultrasonic spectrum, physical, and visual techniques.

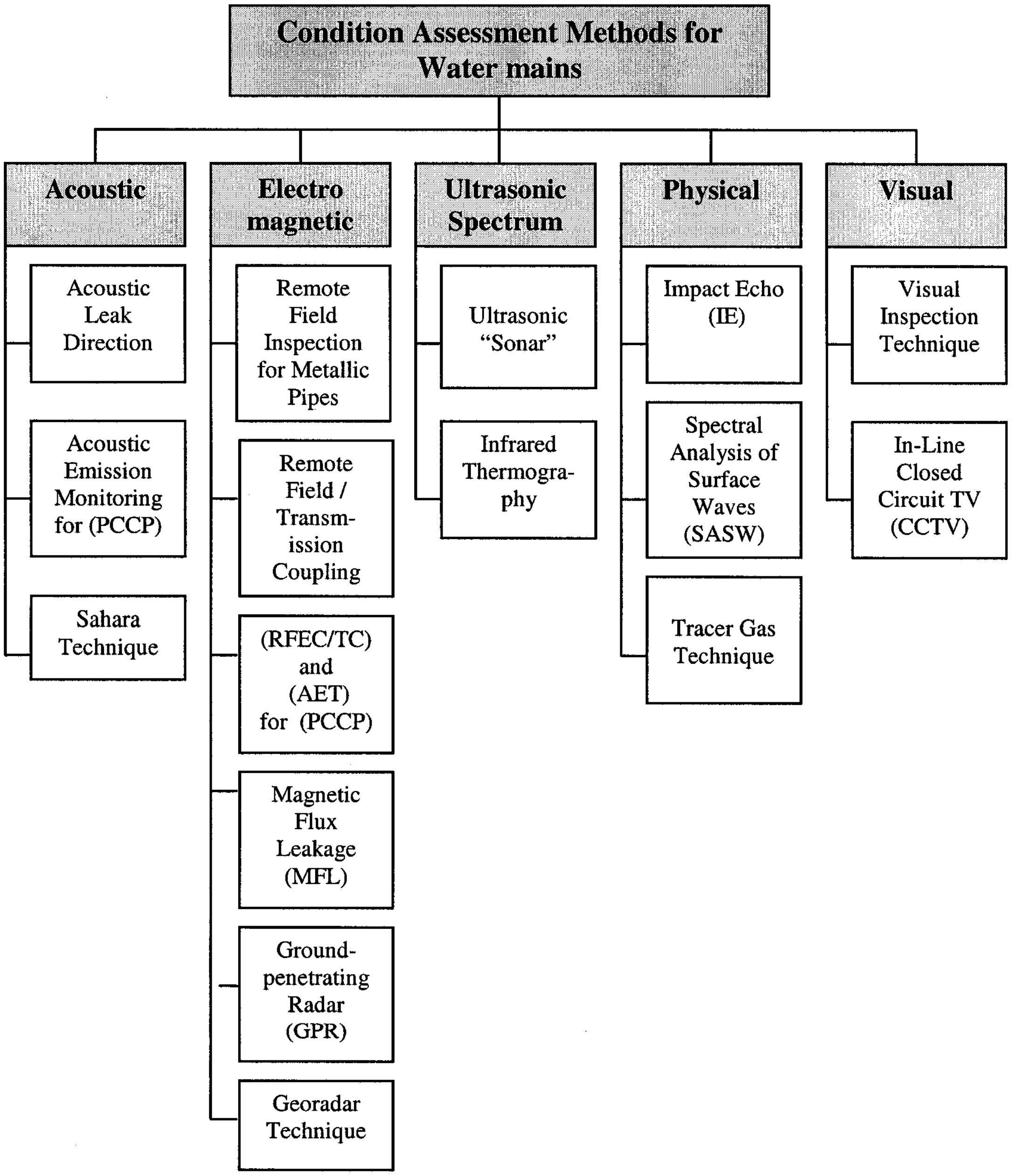

Figure II-3 Destructive and Non-destructive Inspection Techniques for Water Mains

However, little information or advice is available a bout the best methodology to be followed in the usage of these techniques, in addition to the way of selection pipes for inspection. Moreover, the interpretation of the output of these techniques has so far not been verified into pipe condition rating (Makar et al., 2000). Various approaches have been used to inspect and evaluate water distribution pipelines. The following sections describe methods used commercially for evaluating the condition of the existing water mains.

II.4.1.1. Acoustic Leak Direction

This technique is used to detect leaks in the water distribution system. The sound or vibration induced by water, when it escaped from pipes under pressure, is detected by using acoustic equipment. The acoustic equipment consists of listening devices including listening rods, aqua-phones, and geophones. Acoustic equipment should be fixed at contact points with the pipe such as fire hydrants (F.H) and valves, as shown in Figure II-4, in order to be able to listen for leaking sounds.

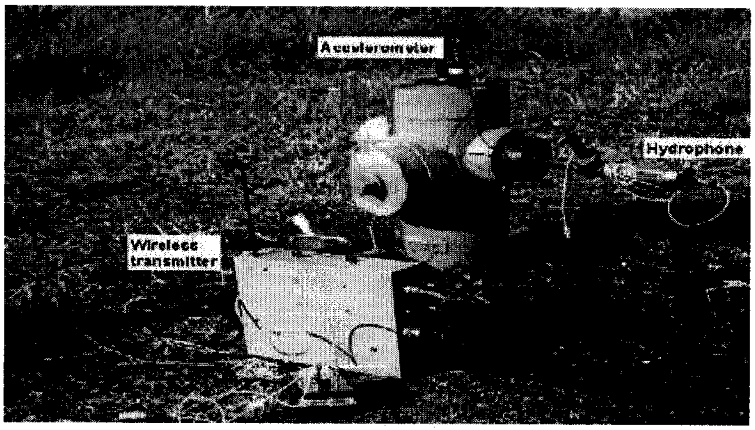

Figure II-4 Leak Sensors Attached to F.H Including an Accelerometer and a Hydrophone (Adapted from IRC, 2003)

The new models of acoustic equipment are a computer-based instrument that has a simple field setup and work by measuring leak signals (sound or vibration) at two points that bracket a suspected leak. By using the cross-correlation method as shown in Figure II-5, the position of the leak is determined automatically based on the calculated time shift between the leak signals. This type of inspection is applicable for all type of pipes (IRC, 2003).

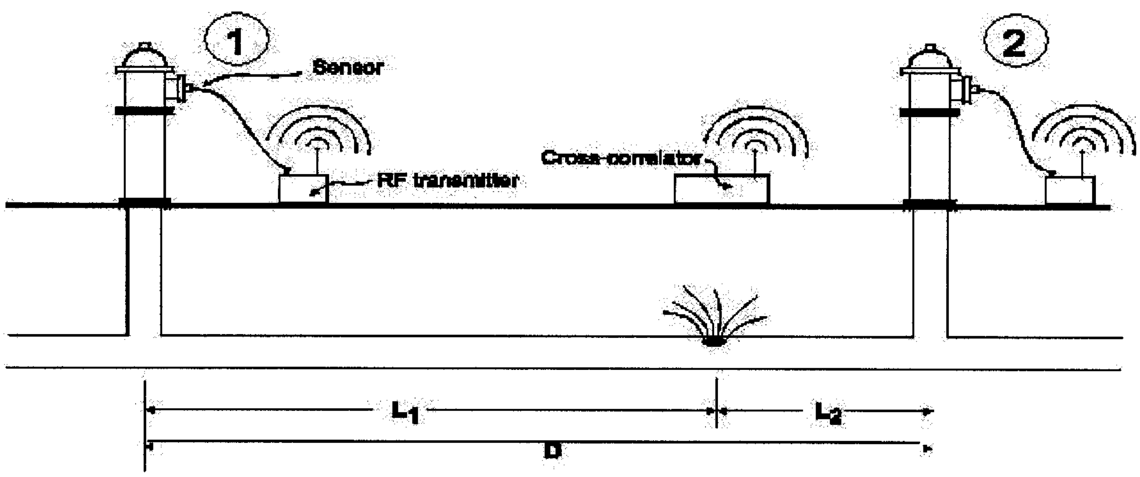

Figure II-5 Schematic Illustration of the Cross-correlation Method (Adapted from IRC,2003)

$T_1 = L_1/V$

$T_2 = L_2/V$

$\Delta T = (L_2 - L_1) / V$

$L_2 = D - L_1 \;\; \text{-->} \;\; \Delta T = (D - L_1 - L_1) / V \;\; \text{-->} \;\; L_1 = (D - V\Delta T) / 2$

II.4.1.2. Acoustic Emission Monitoring (AEM) for (PCCP)

Similar to acoustic leak direction technique is the acoustic emission monitoring, both of these techniques uses hydrophones. But the role of hydrophones in acoustic emission monitoring technique is differing than that for acoustic leak direction. In acoustic emission monitoring, a pair or an array of hydrophones are placed within an operating pipeline to monitor the sounds of pre-stressing wires while breaking, thus the arrival time of these sounds allow for determination of location of their source. By recording the number and rate of breaking wires during the monitoring period, an indication of the overall condition of the pipeline can be considered. Acoustic emission monitoring technique can be deployed and commissioned through existing manholes without the need of dewatering the inspected pipes, as shown in Figure II-6 (Makar et al., 2000; Advitam Inc., 2004)

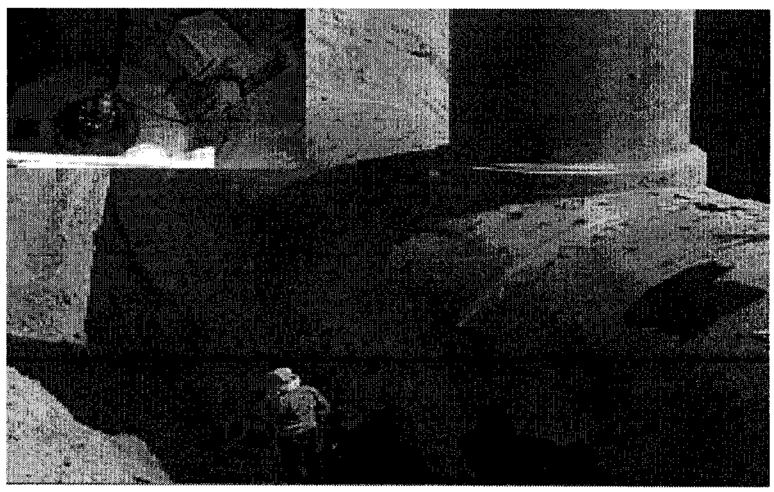

Figure II-6 Acoustic Emission Inspection through Existing Manholes (Advitam Inc., 2004)

II.4.1.3. Remote Field Inspection for Metallic Pipes

Remote field inspection is currently the only inspection technique available that detects damages and determines the condition of gray cast iron and ductile iron pipes before failure. It could also be used for steel pipes (Makar et al., 2000). This technique is currently in use mainly for detecting and determining the condition of small diameter metallic pipes. Tafuri et al. (2002) stated that the application of remote field technique will clarify and provide valuable information about the actual mechanical process of corrosion. Makar et al. (2001) present the process of remote field inspection technique. A circular emitter coil is placed inside the pipe, one or more detector coils or sensor is placed more than 2.5 pipe diameter away from the emitter coil. Passing an alternating current power through the coil produces electromagnetic field reaches the sensor through water or pipe wall as shown in Figure II-7. The signal received through the pipe wall is sensitive to the changes in thickness. This allows corrosion pitting, cracks, and overall wall loss to be detected. However, in order to be able to deploy this inspection technique, the inspected water main sections should be cleaned from tuberculation (Pirnie Inc., 2004).

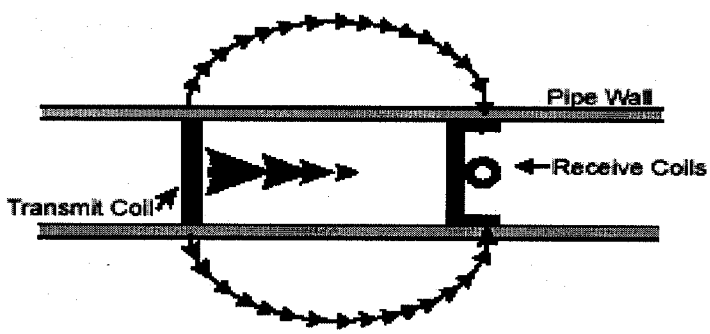

Figure II-7 Schematic of the Remote Field Effect (Adapted from Makar et al., 2001)

Remote field technique provides comprehensive information about the condition of the pipes much more than any other inspection techniques, however it costs much more than other techniques. Thus, if water utilities decide to use this technique for inspection, they have to select the critical sections only to be inspected, rather than inspecting whole system (Makar et al., 2000).

II.4.1.4. Remote Field Eddy Current / Transmission Coupling (RFEC/TC) Inspection for (PCCP)

Remote Field Eddy Current / Transmission Coupling (RFEC/TC) technique provides a baseline of information that identifies and locates wire breaks or ruptures in the PCCPs. This technique is presently available only for use in embedded type PCCP water mains, and used to detect and locate the broken pre-stressing wires within the inspected pipes. Like the remote field inspection technique for metallic pipes, RFEC/TC inspection technique has an emitter and a detector coil that located a distance apart within the pipe. An electromagnetic field is generated inside the dewatered PCCP by the emitter, as shown in Figure II-8. Size of the monitoring equipment can be adapted to monitor pipes from 500mm to 4000mm diameter. Coils interact with the coil of pre-stressing wire in the concrete. The resulting field is measured by the detector coil, measuring the changes because the broken pre-stressed wires will affect the magnetic field. Then, the receiver captures the response to the EM field and the data archived for analysis (Advitam Inc., 2004: Makar et al., 2000).

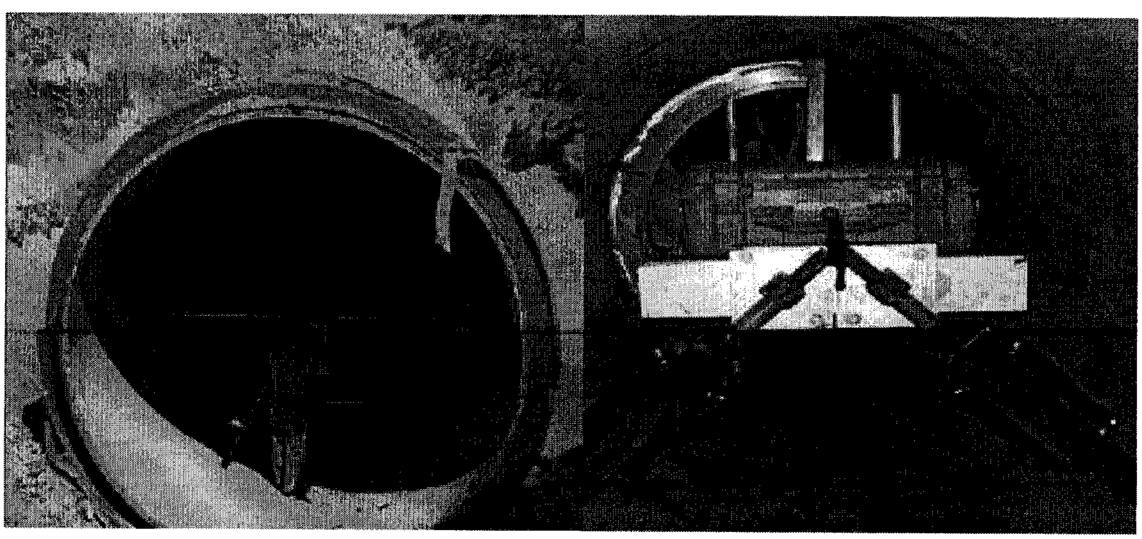

Figure II-8 Monitoring (RFEC/TC) Equipment (Adapted from Advitam Inc., 2004)

II.4.1.5. Remote Field Eddy Current / Transformer Coupling (RFEC/TC) and Acoustic Emission Testing (AET) for (PCCP)

Mergelas et al. (2004) presented and discussed how a combination of two condition assessment technologies, Remote Field Eddy Current / Transformer Coupling (RFEC/TC) and Acoustic Emission Testing (AET) were able to provide high value of information that established the risk of raising the pipeline's operating pressure. The baseline conditions of the pipeline were established by using RFEC/TC. At the same time the pipelines were acoustically monitored AET while changing its pressure to determine the result of increasing the pressure upon the structural integrity of the pipe.

II.4.1.6. Ultrasonic "Sonar"

Ultrasonic technique is used to give information on the quality of any lining inside a pipe, which is not possible by using the remote field effect. The remote field effect is unaffected by the presence of tuberculation inside a pipe, while ultrasonic inspection is impossible where tuberculation is present. This technique is most likely to be applied on metallic pipes such as ductile and cast iron but is not suitable for asbestos cement pipes. That is because the sound waves are significantly weakened in a deteriorated pipe (Rajani et al., 2004). Sonar technique provides a comprehensive condition assessment of the inspected pipe including pipe-wall deflection, corrosion losses, and cracks/pits in the cross-section of the pipe wall, and condition of backfilling surround the pipe. (Allouche et al., 2002). It is based on measuring the transit times for sound waves that travel through the pipe walls and back as shown in Figure II-9. An ultrasonic pulse is generated by a piezoelectric transducer. The pulse velocity depends on the composition and maturity of the material and its elastic properties (Rajani et al., 2004)

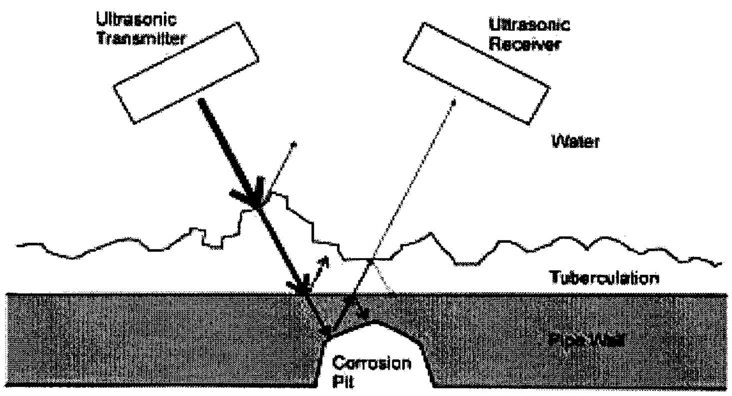

Figure II-9 Ultrasonic arrangement in metallic pipe (Adapted from Rajani et al., 2004)

Variations in the amount of energy and the period of time with the reflected signals are used to estimate the location and generate a complete profile of the pipe surface. The profile is presented as a graphic color image (Allouche et al., 2002; Ratliff, 2003). The accuracy of results varies according to the diameter. For example, when the diameter of the inspected pipe is 200mm, the accuracy has a tolerance of less than 1mm, whereas in larger diameters, the accuracy at 9 ft is approximately 12 mm (Hydromax, 2004).

II.4.1.7. Visual Inspection Technique

It is the most elementary inspection method, depending on technician vision. Visual inspection involves the physical inspection of the pipe's exterior or interior by trained technicians. For exterior inspection, part of the water main is exposed. Then, technician inspect and evaluate condition of bedding, evidence of leakage, condition of external coating, and evidence of external corrosion. For interior inspection, three or more technicians enter the water main, one of them looks for visible cracks, the second sounds the pipe to find areas of delaminating, and the third records type of defects and location. However, this technique is becoming less popular because of the high labor costs and safety problems. Moreover, exterior visual inspection is limited by the diameter of the water main being inspected (Allouche et al., 2002).

II.4.1.8. In-Line Closed Circuit Television (CCTV) Inspection

Closed Circuit Television (CCTV) inspection technique provides visual information about the condition of the interior surface of the inspected pipe. In this technique a CCTV mobile camera is attached to a mobile robot inserted into water main and connected to a monitor that allows the operator monitoring and type any kind of information on the upper right corner of the image (i.e. diameter, defect type, location, etc.). A mini push camera may be also used when there are limitations such as small diameter pipes or sharp bends, as shown in Figure II-10. Cameras are either fix type or pan and tilt cameras (Allouche et al., 2002; Tafuri et al., 2002).

However, in order to be able to perform in-line CCTV inspection, the water main sections should be isolated, cleaned and dewatered to allow for detecting interior defects efficiently. But if the water main is heavily tuberculated, pipes can be cleaned using a chain-flail or a high-pressure pigging system (M. Pirnie, 2004). The success or failure of results in this technique is subjected mainly on the operator's level of inspection knowledge and experience (Allouche et al., 2002; Tafuri et al., 2002).

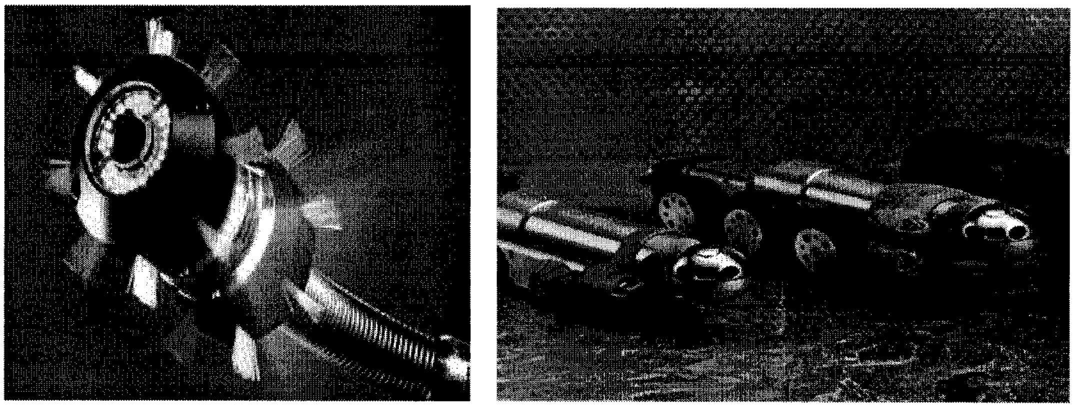

Figure II-10 Mini Push Camera and CCTV Tilt Camera Mounted on All Wheel Drive Tractor (Adapted From Pearpoint Inc., 2004)

II.4.1.9. Tracer Gas Technique

This is a non-toxic technique and is used to detect leakage in the water system. This technique is done by injecting a lighter-than-air gas, such as helium or hydrogen, into an isolated section of water system. If there is leak, the gas will escape and permeates through the soil and pavement to the surface. Then, a high sensitive gas detector is used to locate the leak position by scanning the ground surface directly above the pipe (Hunaidi, 2000).

II.4.1.10. Magnetic Flux Leakage (MFL)

This technique is commonly applied in the gas and oil pipeline industry to inspect and locate pipeline defects. It is currently not applied for inspecting metallic water pipes (cast iron, etc.). Magnetic flex leakage technique (MFL) is used to detect internal and/or external corrosion pits. It is based on a saturating magnetic field, which is supplied by huge magnets, that is placed inside the pipe to magnetize pipe's wall to near saturation flux density that generates a steady magnetic field, as shown in Figure II-11. If corrosion pits or cracks are available, a small amount of this field will come out of the pipe wall. Then, the leakage field is measured and recorded by sensors, (i.e. Hall probes or induction coils), moving with the MFL (Queen's Univ., 2005).

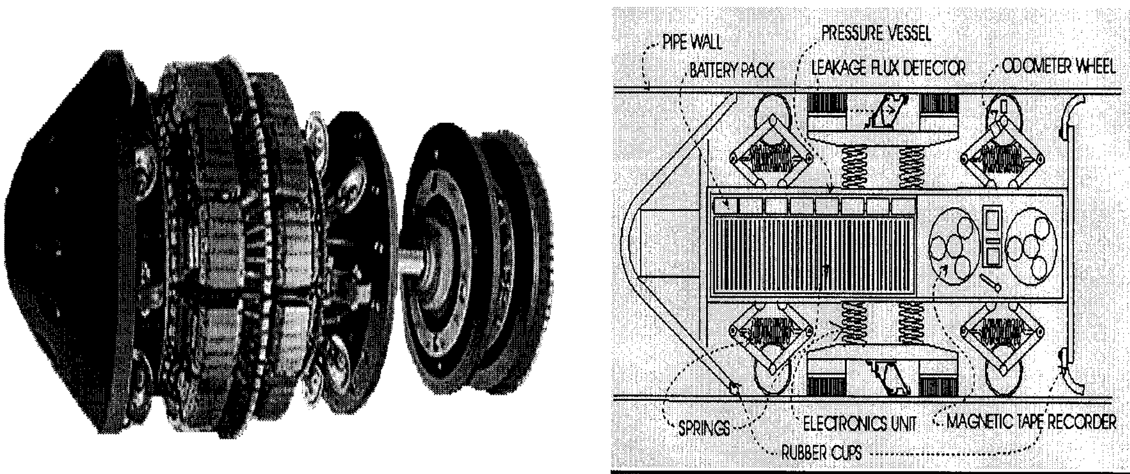

Figure II-11 Schematic Drawing for MFL Testing Equipment (Adapted from Queen's Univ., 2005)

(MFL) inspection technique has the ability to provide very detailed signals. However, converting these signals to accurate estimates of size need an expert who understands the effects of inspection conditions and the magnetic behavior of the different type of steel pipe used. It should be noted that the developed MFL technique can only be applied in cleaned and unlined water pipes (Queen's Univ., 2005; Makar et al., 1999).

II.4.1.11. <u>Impact Echo (IE) and Spectral Analysis of Surface Waves (SASW)</u>

Impact Echo (IE) and Spectral Analysis of Surface Waves (SASW) techniques have been successfully applied to the inspection of metallic pipes, asbestos cement pipes and concrete pipes to detect corrosion pits, voids and cracks but not their extent. To be able to apply these techniques, pipeline should be dewatered and the internal pipe walls have to be fairly clean. These techniques is based on a source of controlled impacts, such as a falling weight or a large pneumatic hammer, applied to the wall of the pipeline and produces low frequency surface waves which are detected by the geophones, that are mounted against the pipeline wall as shown in Figure II-12.

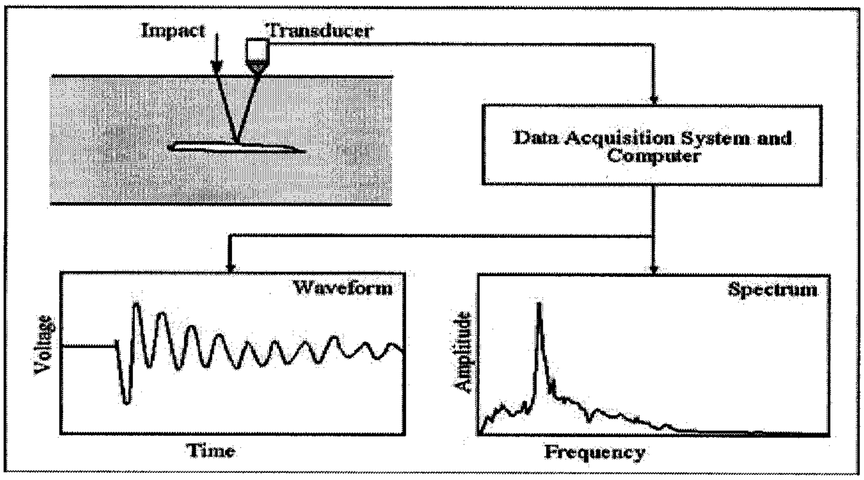

Figure II-12 Schematic Diagram for Impact-Echo Technique (Adapted from Impact LLC, 2004)

When geophones receive high frequency sound, it signifies that there is no pipe wall deterioration. While if they receive low frequency sound, it signifies that the pipe wall is deteriorated or delaminated.

The main difference between the two techniques, IE and SAWS, is that impact echo is looking only at the actual produced waveform, while spectral analysis of surface waves is using more geophones and separating the waves into different frequency components that travel at different speeds and penetrate the soil beyond the pipe at different depths. Therefore, SASW technique allows gathering more information about the condition of the pipe and the surrounding soil. It should be noted that cleaning of the pipe walls is required before applying any of these techniques (Makar et al., 1999; Rajani et al., 2004).

II.4.1.12. <u>Infared Thermography</u>

This technique is considered effective in detecting leaks and inspecting backfilling surround the pipe by displaying image that use range of intense colors to detect areas of varying temperature. It is a non-contact inspection technique. The process of inspection in this technique is based on measuring the thermal variations over specific area, where the pipe exists. When the water pipe is leaking, the thermal characteristic of the adjacent soil is affected. Then, by using handheld or vehicular airplane-mounted infrared cameras, the resulting thermal variance above pipe can be detected (Hunaidi, 2000). Inspection results are displayed and recorded on a monitor that allows both the operator and the engineer to review these results at a later time, as shown in Figure II-13.

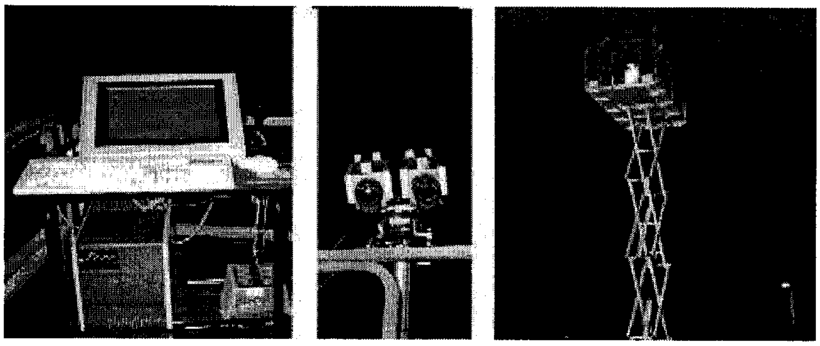

Figure II-13 PC-Based Control Unit, Dual-Wavelength Infrared Cameras, and Lift Used to Elevate Infrared System (10 m) Above Ground Surface (Adapted from IRC, 2003)

If this technique applied in areas congested with other services, the output results can not be analyzed easily. Infared Thermography technique is easily affected with the surrounding weather conditions such as rain and snow that tend to cover the heat signature of a leak (Ratliff, 2003). The main disadvantages of this technique that it relies heavily on the operator's experience to interpret the results, also it can not discover whether the void is a result of soil loss or is avoid in structure such as water valve box. Moreover, it doesn't indicate the size of the void (Allouche et al., 2002; Ratliff, 2003).

II.4.1.13. Ground-Penetrating Radar (GPR)

Ground-Penetrating Radar (GPR) technique is used to locate leaks in the existing water pipes. It detects voids in soil grains that are created surround the pipe due to water leakage, or detects parts of the pipe that look deeper than they actually are. The GPR emits pulses of radio waves into the ground and measures the strength and delay time of the reflection and refraction waves by subsurface layers or buried objects. When GPR waves encounter variance in dielectric properties such as a void or pipe, these waves are partially reflected back to the ground. Then, it forms an image by radar time-traces that can be obtained by scanning the ground surface. The depth of the reflecting object is determined based on the time lag between transmitted and reflected radar waves (Hunaidi, 2000).

GPR has little effectiveness for soils with high electrical conductivity such as clay soils, because the high conductivity soils will cause severe attenuation of the GPR signals, and hence restricting penetration depth. GPR technique could be combined with sonar and CCTV techniques to detect defects around water pipes, and conjunct with infrared thermography technique (Allouche et al., 2002; Ratliff, 2003).

II.4.1.14. <u>Georadar Technique:</u>

Georadar technique has been used extensively for inspecting sewerage pipes. Recently, tests are undergoing to check its applicability to non-metallic water mains, such as asbestos cement pipes. Presently, it has the ability to inspect only the external face of the pipe, so in order to be able to apply this technique the pipes need to be uncovered just at specific locations. Georadar technique is based on measuring the transit time and signal strength attenuation of electromagnetic impulses as they travel through a pipe wall thickness and back, as shown in Figure II-14.

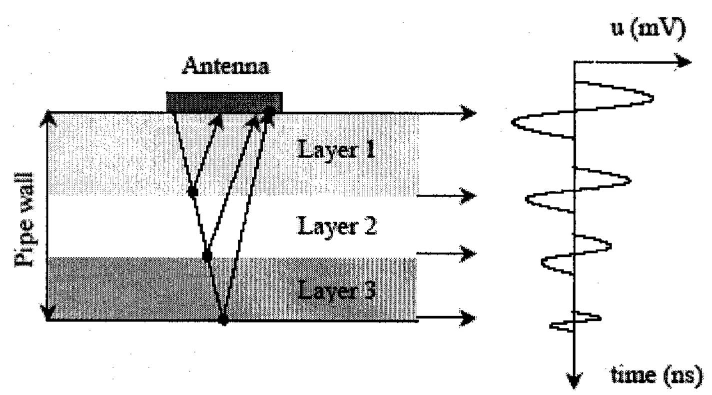

Figure II-14 Georadar Arrangement in Asbestos Cement Pipe (Rajani et al., 2004)

Each layer thickness is determined based on travel times and signal strength, and in addition to the electrical properties of each layer (Rajani et al., 2004).

II.4.1.15. <u>Sahara</u>

Bond et al. (2004) described and introduced the development and distribution of Sahara technique. It is a non-destructive condition assessment technology that identifies the location and estimates the magnitude of leaks in large diameter water transmission mains of any construction types, ranging from 300mm diameter and above. Sahara can be inserted into a live transmission main that needs to be inspected, through any tap of 2 inch size or greater in diameter, as shown in Figure II-15. Therefore, no isolating or dewatering is required. Sahara is so sensitive and accurate. It can detect leaks as small as 0.25 US Gallon/hr through identification of the distinctive acoustic signals generated by leaks in the pipe wall, the joints or steel welds. In addition to above, it can accurately locate locations of leaks within inches, since the sensor head can be stopped once the leak has been detected. Pipelines up to 6,000 ft. can be inspected with a single insertion. By using Sahara technique, municipalities and utilities can reduce non-revenue water and avoid the cost of whole pipe replacement, and hence extending the life of their pipeline.

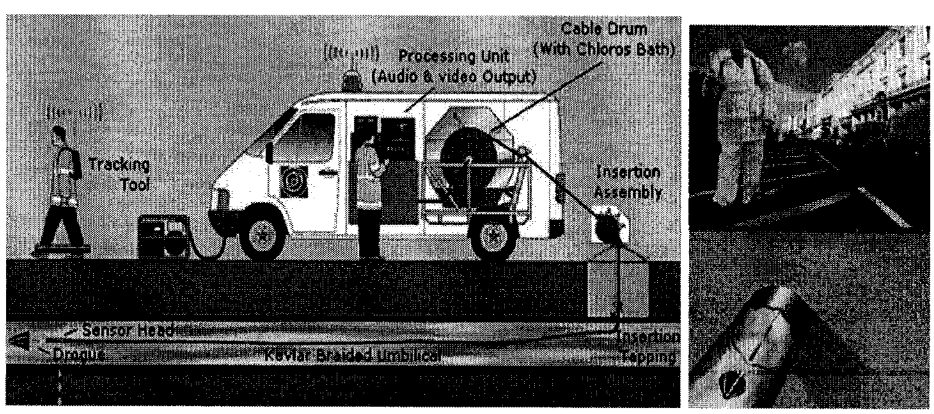

Figure II-15 Schematic of the Sahara System in Operation (Adapted from Bond et al., 2004)

Based on the previous literature, it is noticed that selecting the appropriate inspection method provides the engineers with valuable information which assist in planning maintenance and rehabilitation activities. Yet, none of these techniques is able to provide a comprehensive evaluation of pipe condition. Rajani and Kleiner (2004) stated that the majority of developed inspection techniques are based on non-destructive (NDT) methods but none of these techniques are able to exactly inspect the existing pipes in order to identify and recognize all the distress indicators, as shown in Table II-4. In addition, the output interpretation of these techniques has not been interpreted into pipe condition rating.

Table II-4 Summary of NDE technologies applicable to different pipe materials (Adapted from Rajani et al., 2004)

NDE method for structural defects	AC	Concrete	Ductile/ cast iron	Steel	PVC/PE	Availability for water/other pipes	Dewatering requirement
Visual (direct/remote)	√; LC	√; LC	?; HC	?; HC	?; LC	yes/yes	not necessary
RFEC	×	?	√; MC	√; MC	×	yes/yes	not necessary
RFEC/TC	×	×	×	×	×	yes/no	no
Magnetic flux leakage	×	×	?; HC	?; HC	×	R&D/yes	not necessary
Ultrasonic	?	×	√; M/HC	√; M/HC	?; LC	R&D/yes	not necessary
Impact echo (IE)	√; LC	√; LC	×	×	×	yes/yes	no
Georadar	√; NC	?	?	?	?	yes/no	no

× : not applicable; √: available; ?: may/may not work;

Cleaning requirements: LC: light; MC: moderate; HC: heavy; NC: none

II.4.1.16. Techniques used to Evaluate Other Infrastructures

Various approaches which have been used to inspect and evaluate other infrastructure facilities, (i.e. sewers, roads; gas pipes, and tunnels), are briefly described in Appendix (B). However, most of these approaches have been used in evaluating the condition of water mains.

II.4.2. Indirect Indicators and Statistical Methods

Best Practices (2003b) stated that the best way to preliminary assess the condition of a water distribution system is through analyzing the available data, which should be sufficient to be statistically significant. They specify the type of data that should be used to conduct such analysis based on four common types of problems that can occur in water distribution systems: structural condition, hydraulic capacity, leakage, and water quality problems. The type of data that should be used is summarized in Table II-5. The preliminary assessment will assist municipal engineer in identifying the trends of failure for pipes in water system, and hence be able for locating and prioritizing areas that need more detailed investigation.

Table II-5 Type of Data Used for a Preliminary Assessment (Adapted from Best Practice, 2003b)

Problem	Preliminary Assessment	Reasons For More Detailed Investigation	Detailed Investigation
Structural Condition	• Spatial and temporal analysis of water main breaks • Compilation of soil map • Routine inspection of valves and hydrants • Routine inspection of insulation and heat tracing in northern areas	**Level of Service** • Preliminary investigations indicate an excessive break rate, excessive leakage, inadequate hydraulic capacity and/or impairment of water quality **Cost Effectiveness** • To facilitate capital planning and asset management programs	• Detailed analysis of break patterns, rates and trends • Statistical and physical models • Pipe sampling • Soil corrosivity measurements • Pit depth measurements • Non-destructive testing • Failure analysis • Visual inspection • Thermal analysis (far North)
Hydraulic Capacity	• Low-pressure complaints • Hydrant flow tests • Rusty/coloured water occurrences • Visual inspection of pipe interior • Monitoring of pressure and pumping costs	• Pilot testing of new technologies to facilitate long-range planning support • Opportunistic work, such as when a water main is temporarily out of service	• Hazen-Williams C factor tests (pipe roughness) • Computer modelling
Leakage	• Water use audit • Per capita water demand • Routine leak detection survey	**Risk Management** • Risk analysis identifies critical water mains that have a high potential for significant property damage, environmental impact or loss of service	• Leak detection survey • Detailed limited area leakage / demand assessment
Water Quality	• Water quality complaints • Routine sampling data • Results of flushing program	• Due diligence (e.g., failure analysis of a failed critical water main)	• Detailed water quality investigation • Computer modelling

II.4.2.1. Structural Condition

A preliminary assessment of structural condition in a distribution system is based on analyzing the total number of breaks/year. However, the acceptable total number of breaks/year varies from one municipality to another. The location of all breaks can be presented on a geographic information system (GIS) map to verify areas with higher break frequency than others. It can also be presented on a global positioning system (GPS) map to conduct spatial analysis. That is done by overlaying break records location on a soil map to verify the correlation between soil types and break frequency (Best Practices, 2003b).

II.4.2.2. Hydraulic Capacity

A preliminary assessment of hydraulic capacity in a distribution system is based on analyzing low-pressure complaints and hydrant-flow test results. The analysis of the collected data will show the trend of hydraulic capacity changing through the distribution system over time and how it varies spatially. If the numbers of low-pressure complaints or low fire flows records are increased over the time, it indicates that the hydraulic capacity of a system is deteriorating. That is due to tuberculation in the mains or partially closed isolation valves (Best Practices, 2003b).

II.4.2.3. Leakage

Best Practices (2003b) reported that leak detection can be an important tool to determine the deterioration of water distribution systems. Leakage testing technique is based on determining the amount of leakage from the mains at a known pressure. The most common methodologies that are used to detect the leakage of the water system are hydrostatic leakage test and water audits. They have been applied in the past to significant portions of or entire water distribution systems;

<u>Hydrostatic Leakage Test</u>

The testing is done by isolating the system into zones or pipeline segments, and measuring the amount of water added to the mains to maintain the test pressure which varies according to working pressure of the inspected pipeline. Then, the rate of leakage is measured. If the rate of leakage is more than the expected allowable leakage rate according to specification; then there is a pipe failure (Comeau et al. 2000; Makar et al., 2000).

<u>Water Audit</u>

The City is divided into sections. For each section, total consumption is measured, and the total industrial consumption and consumption/hour hold is evaluated. The difference is an indication of existence leaks. It can be combined with leak detection approach. In some cases the water audits are performed and organized continually with automatic data recording system in order to facilitate quick repairs for the leaking pipes (Makar et al., 2000).

II.4.2.3.1. *Water Quality*

A preliminary assessment of the water quality in a distribution system is based on analyzing the water quality complaint records and routine water quality monitoring data. The analysis of the collected data will show the trend of water quality changing through the distribution system over time and how it varies spatially. Chlorine residuals and concentration of iron in water are used as a measure for water quality. When chlorine residuals are decreased in some areas of water system, it indicates that these areas are deteriorating. Likewise, the concentration of iron is increased in water indicates the degree of internal corrosion of unlined metallic mains (Best Practice, 2003b).

II.5. CONDITION RATING AND DETERIORATION MODELS FOR WATER MAINS

Pipes in a water distribution network are characterized by increasing the frequency of breakage and failure overtime mainly due to deterioration, which would reduce the hydraulic network capacity and the quality of service. It would also increase operation and maintenance costs and water losses in the water distribution system. Al-Aghbar and Moselhi (2005) stated that the causes of water mains deterioration is due to four main reasons; aging of water distribution infrastructure due to the surrounding environmental factors, inadequate preventive maintenance and asset management programs, inadequate funds and changed municipality priorities, and finally lack of information and staff. Recent researches have reported an increase of the breakage rate in water mains. Najjaran et al. (2004) reported that almost 700 water main breaks are reported in North America everyday, which account for maintenance costs of about $1 billion/year. Al-Aghbar and Moselhi, (2005) also reported that 40% of Canada's potable water is lost due to leakage and deterioration of water mains, and these water mains have deteriorated by about 35% over the past 10 years.As a result, several models have been developed and improved to predict deterioration in water mains. Deterioration rate in water mains is affected by different physical, environmental and operational factors, as shown before, some of these factors are included in the developed deterioration models.

II.5.1. CONDITION RATING MODELS

The purpose of a condition rating system is to objectively rate or scale the current condition of the buried pipes. Yan et al. (2003) proposed a methodology that assists engineers in prioritizing pipe inspection and pipe rehabilitation in water systems. It uses Fuzzy Composite Programming (FCP) to aggregate the individual pipe condition indicators into a final overall indicator. The method of FCP is based on multi-criteria decision making (MCDM) techniques with fuzzy sets theory. The FCP hierarchical structure is deployed to combine first-level fuzzy indicators that lead pipes to deteriorate including pipe age, pipe diameter, pipe material, road loading, soil condition, and surroundings (environmental conditions), into second-level fuzzy indicators including pipe physical factors and environmental factor, as shown in Figure II-16.

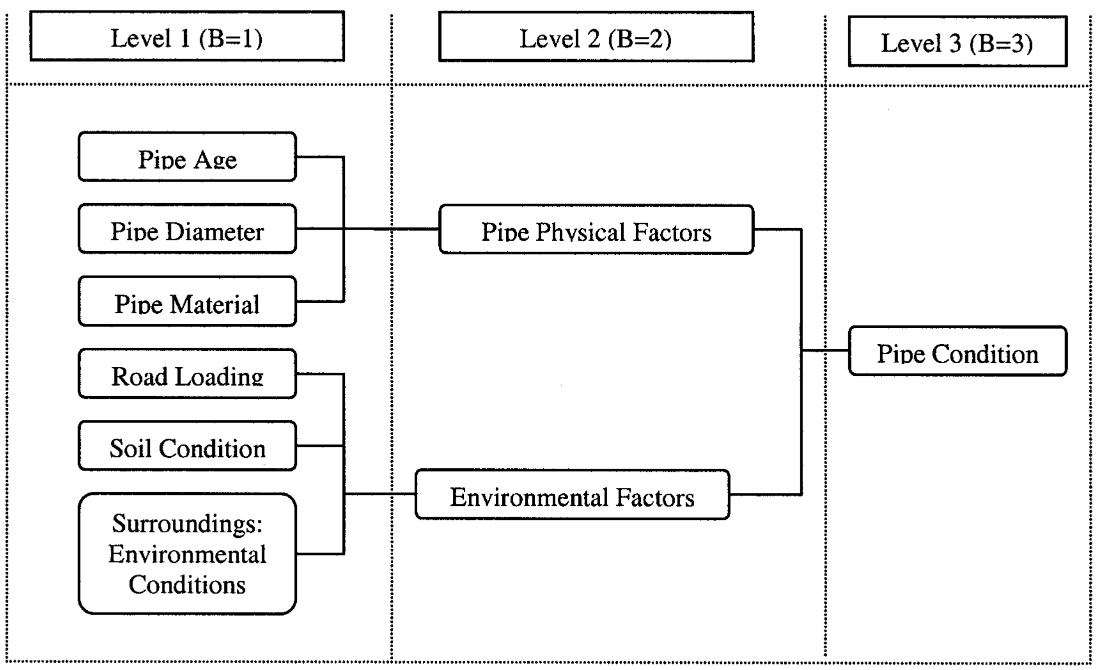

Figure II-16 Pipe Condition Assessment Composite Structure. (Adapted from Yan et al., 2003)

By using FCP hierarchical aggregation process, the final level fuzzy indicator, which is the pipe condition indicator, is achieved. The final level indicator is used as criteria to rank the pipe's condition. A fuzzy ranking method is applied to rank the fuzzy number and convert fuzzy results into crisp numbers. The ranking values are ranging from "0" to "1". The limitation of the developed model is that it covers only the physical and environmental factors. It also considers one type of pipes which is cast iron as lined and unlined. In addition, the developed model considers one type of soil. Geem (2003) developed a decision support system (DSS) for pipe condition assessment using back-propagation neural network (BPNN) technique, but the data used in developing the model was arbitrary generated. The developed BPNN model is trained based on seven input factors including pipe material, bedding condition, corrosion, temperature, trench width, pipe diameter, and pipe age. The out put of the model is the condition rating which scaled from "0" to "1". "0" value indicates that the pipe is in perfect condition, and "1" value indicates that the pipe in poor condition. Concurrently with our research, Najafi and Kulandaivel (2005) developed a neural network (ANN) model for predicting the condition of sewer pipes based on the historic condition assessment data. Seven input variables used in the developed model including length, size, type of material, age, depth, slope, and type of sewer. The out put of the model is the condition rating which scaled from "1" to "5". "1" value indicates that the pipe is in perfect condition, and "5" value indicates that the pipe in poor condition. However, model validation is not done.

II.5.2. DETERIORATION MODELS

Significant research effort has been carried out in the last two decades to model infrastructure deterioration. Different deterioration models have been developed to facilitate the prediction of asset condition and the possibility of failure in future.

II.5.2.1. Physical / Mechanical Models

Rajani and Kleiner (2001) provide a comprehensive literature overview and criticism for the developed mechanical models, which are divided into two groups, deterministic and stochastic models. These models are appropriate to be applied for major transmission water mains. These physical mechanisms include three main aspects: (1) pipe structural properties (i.e. material type, pipe-soil interaction, and quality of installation); (2) internal loads due to operational pressure and external loads (i.e. soil overburden, traffic loads, frost loads and third party interference); and (3) material deterioration due largely to the external and internal chemical, bio-chemical and electro-chemical environment.

II.5.2.2. Statistical Models

Kleiner and Rajani, (2001) present a comprehensive literature overview and criticism for the developed statistical models which are classified mainly into 3 groups; deterministic, probabilistic multivariate, and probabilistic single-variate models. These models are appropriate to be applied for water distribution networks. They are used to quantify the structural deterioration of water mains based on analyzing various levels of historical input data, which identify pipe breakage patterns, and hence predict the breakage rate of a water main.

Based on the previous, it is noticed that data gathering and statistical models can be developed to pre-investigate the condition assessment of water mains, and hence, if there is a potential critical water main situation, a direct inspection method can be introduced to perform more investigation for better solutions and comprehensive understanding of pipe condition; however, they are more expensive.

II.6. ARTIFICIAL NEURAL NETWORK (ANN)

II.6.1. Overview

In real world situations, the collected data are either noisy or incomplete. So, the main challenge for decision maker is using these available data to make reasonable predictions. In such situations, the artificial neural networks (ANN) technique may provide predictions based on that available information. The ANN technique mimic the ability of the human brain in predicting patterns based on learning and recalling processes. ANNs are considered very effective and predictive tools because of its ability to learn automatically by example. Sadiq et al. (2004) stated that ANNs are modeling techniques that are useful for data-based hypothesis development in areas where causal relationships among variables are unknown. Sawhney et al. (2002) affirm that ANNs modeling techniques are useful to represent problems where solutions are not clearly articulated or where the relationships among inputs and outputs are not adequately identified. ANNs consist of large number of artificial neurons that are randomly arranged and connected in different layers (Input, hidden, and output). The hidden layers are connected to input and output layers; thus, they are not connected to external world (Black box) (Zayed and Halpin, 2005).

II.6.2. Artificial Neural Network (ANN) Application

ANN theory has been widely used and applied in different fields of engineering researches because of its ability to learn automatically by example, and to nonlinearly relate independent and dependent variables. ASCE, (2000) reported that the Artificial Neural Network (ANN) is a good methodology that can be used to assess the existing pipe condition without excavation. So, many researchers applied the ANN methodology to predict underground pipes condition. ANN technique has been applied to water distribution network of a sub-division in Edmonton, Canada (Rajani and Kleiner, 2001). It considered the complete network as a single unit. It was trained with historical input data including temperature, rainfall, operating pressure, and number of breaks. However, some main physical and environmental factors were not included in the model such as pipe age, type, diameter, and soil properties. A decision support system (DSS) for the pipe condition assessment was developed by (Geem, 2003) using ANN approach, but the data used in developing the model was arbitrary generated. Geem model is trained based on seven factors including pipe material, bedding condition, corrosion, temperature, trench width, pipe diameter, and pipe age. An ANN is used by (Ardakani, 2004) to detect pipelines damage in water distribution systems due to earthquake. Broad et al. (2005) used ANN meta-models for estimating common risk measures for water distribution systems performance, such as hydraulic and water quality reliability and vulnerability. Wanakule et al. (2005) developed an ANN model for water system management that provides accurate short-term prediction for ground water level into few days. In sewers, Moselhi and Shehab-Eldeen (2000) deployed the Back-Propagation Neural Network (BPNN) in the analysis and classification of defects in underground sewer pipelines. The ANN was trained to classify four different types of defects including cracks, joint displacements, reduction of cross-sectional area, and spalling. Najafi and Kulandaivel (2005) developed an ANN model for predicting the condition of sewer pipes based on the historic condition assessment data. Seven input variables used in the developed model including length, size, type of material, age, depth, slope, and type of sewer.

In addition to above, the ANN technique is used in different fields of civil engineering researches including project management. Portas et al. (1997) applied the ANN technique to develop a model for estimating the construction productivity. AbouRizk et al. (2001) suggested and discussed an approach that enables an estimator to produce accurate labor production rates (labor/unit) for industrial construction tasks such as welding and pipe installation based on various factors including general project characteristics, site characteristics, labor characteristics, equipment characteristics, difficulty characteristics, and other activity characteristics. Zayed and Halpin (2005) developed a model to assess productivity, cycle time, and cost for pile construction using the ANN technique. Hegazy and Ayed (1998) deployed the ANN technique to manage construction cost data and develop a parametric cost-estimating model for highway projects. Wilmot and Mei (2005), also, developed an ANN model to estimate the overall highway construction cost. Tarefder et al. (2004) used the ANN for evaluating the rutting performance of asphalt pavement. Then, Tarefder et al. (2005) constructed and applied neural network to determine a mapping associating mix design and testing factors of asphalt concrete samples with their performance in conductance to flow or permeability. Chou and Pellinen (2005) used the ANN methodology to develop time-dependent roughness prediction models for three types of pavements: Portland cement concrete pavement, asphalt overlay over concrete pavement, and asphalt pavement. Dikmen et al. (2005) proposed an ANN model that can be used as a tool to assess company effectiveness and guide decision makers about the major determinants of organizational effectiveness to increase firm performance. Moreover, a prototype integrated crane selection tool (*IntelliCranes)* is developed by (Sawhney et al, 2002) that uses ANN technique to process the subjective information needed for crane type selection in a consistent manner.

II.6.3. Back-Propagation Neural Network (BPNN) Technique

The Back propagation algorithm was first proposed by Paul Werbos in 1974, but it became widely used until it was re-discovered by Rumelhart and McClelland in 1986 to address the learning problem for multilayer networks. Back propagation neural networks (BPNN) are one of the most common neural network structures, as they are simple and effective, and have been used in different fields of researches. Similar to all neural network paradigms, a BPNN learn by example and can be used to make predictions. Artificial neurons receive information from other neurons, process it, and then send the filtered information to the other neurons (Tsoukalas and Uhrig, 1997).

BPNN consists of at least three layers: an input layer (*n)*, at least one hidden layer (*h)*, and an output layer (*m*), as shown in Figure II-17. Units are connected in a feed-forward fashion with input neurons fully connected to neurons in the hidden layer, and hidden neurons fully connected to neurons in the output layer. Each neuron receives weighted inputs from other neurons and communicates its outputs to other neurons by using an activation function. The following is brief description for each layer (i.e. Chou and Pellinen, 2005; Moselhi and Shehab-Eldeen, 2000; Tsoukalas and Uhrig 1997);

Input layer: contains the input neurons, which receive the information and the values of the input pattern.

Hidden layer: contains the hidden neurons which processes the incoming information based on the stored experience through training. That is done by receiving the weighted values of the input neurons, and computes the value to send to the output neurons. The values of the hidden neurons and the weights of the connections form the internal representation of the network are completely computed by the network, without human interference. The hidden layer contains unknown knowledge (Black box) of the relations lie between different patterns.

Output layer: the output neurons in the output layer receive the weighted output of the hidden neurons and then compute the output filtered pattern.

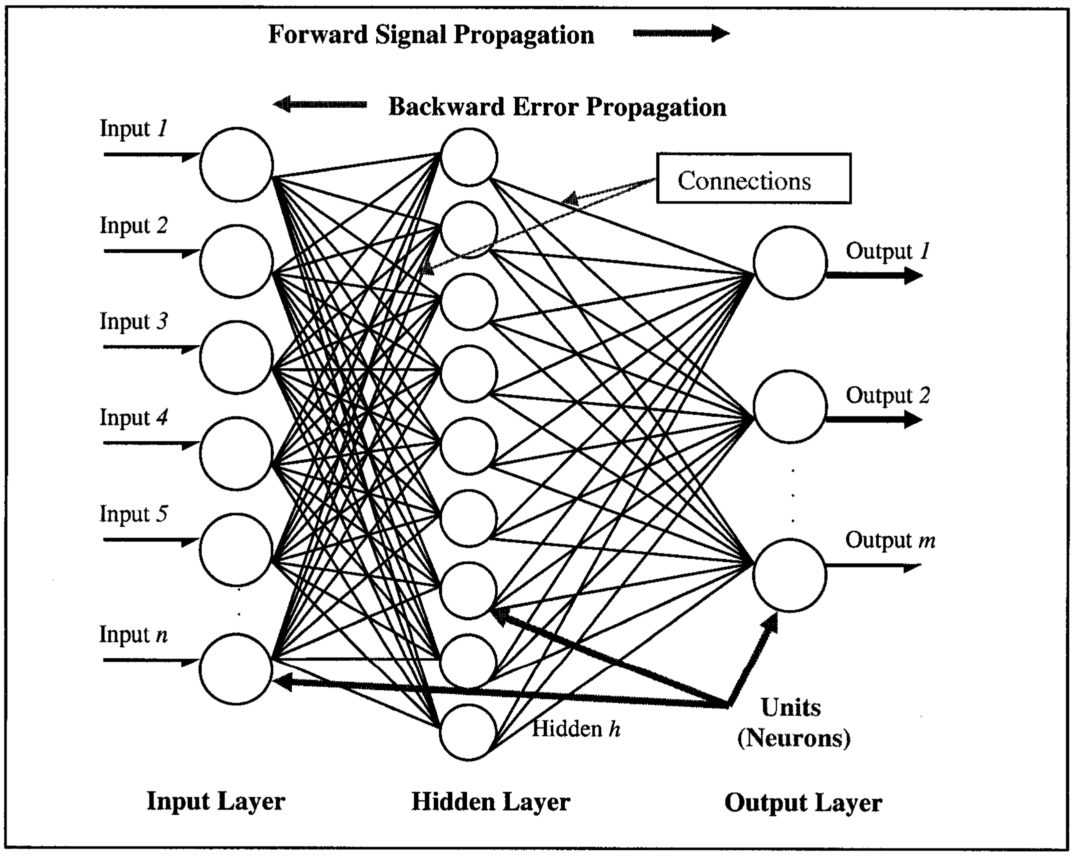

Figure II-17 Schematic Architecture of the (BPNN) with one Hidden Layer

II.6.4. (BPNN) Learning and Recalling Processes

In General, Back-propagation neural network uses a supervised learning algorithm (the output is provided to the ANN to train itself) to perform learning and recalling processes (Tsoukalas and Uhrig, 1997; Zayed and Halpin, 2005). Learning process involves training the network on a known data set of input–output pairs. The input pattern is presented to the network and then an output pattern is estimated. Then, the estimated output pattern is compared to the actual output pattern resulting in an error value. Then, the error value is backward propagated through the network, and the values of the connection weights between the layers are adjusted to enhance its prediction accuracy. Hence, in the next learning cycle the output pattern will be more similar to the actual output pattern. This process is repeated until estimated output pattern and actual output pattern are equal or almost equal, or until the specified allowable error limit is reached. Once ANN is trained, the ANN can be used to solve problems similar to the ones it was trained on through recalling process. The input pattern is feed forward producing an output pattern based on the computed ANN weight structure that is trained during the learning process.

It should be noted that learning rate for network is specified by the designer of the model. The learning rate is defined as the rate of which ANN will learn patterns in the training data set, or the amount of adjustment applied to the old weight. For example, if the learning rate set to be (0.01), then it will take 100 patterns to make a 1% adjustment. Lower learning rate requires more training iterations, while higher learning rate allows the network to converge and learn quickly.

II.6.5. (BPNN) Validation Process

After a BPNN network has learned the correct prediction for a set of inputs, it can be validated by testing the developed model on unknown testing data set to find out how well it predicts untrained patterns. The evaluation and validation of an ANN prediction model can be done by using common error metrics such as the mean absolute error (MAE), root mean squared error (RMSE), or mean absolute percentage error (MAPE) (Dikmen et al., 2005), or by using the average validity percent (AVP), which shows the validation percent out of 100, and the average invalidity percent (AIP), which shows the prediction error to validate the developed ANN model (Zayed and Halpin, 2005).

II.7. ANALYTIC HIERARCHY PROCESS (AHP)

II.7.1. Overview

Analytic hierarchy process (AHP) is defined as a general theory of measurement (Saaty, 1991). It is an easy mature technique that attempts to simulate human decision process. The AHP technique was developed by Dr. Saaty more than 20 years ago. The intention of developing the AHP model is to assist decision makers in solving complex problems by organizing thoughts, experiences, knowledge and judgments, into a hierarchical framework, and guiding them through a sequence of pair-wise comparison judgments. The hierarchical structure presents the relationships of the goal, criteria, sub-objectives, and alternatives (outputs). Moreover, the AHP allow decision-makers incorporate both qualitative and the quantitative considerations of human thought and intuition, which utilized in a logical fashion. The qualitative is to define the problem and its hierarchy, and the quantitative to articulate judgments and preferences concisely. Briefly, the AHP provides decision-makers with logical decisions based on analytical methods which eliminate the chances of challenging in decision making.

II.7.2. Analytical Hierarchy Process (AHP) Application

Analytical hierarchy process (AHP) theory has been widely used and applied in different fields of theory and practice. It has been applied in multicriteria decision making, in planning and resource allocation, in conflict resolution, and in prediction problems (Saaty, 2001). Dey (2003; 2004) develop a risk-based model based on the AHP technique to identify the factors that influence failure on specific portions of petroleum pipelines and analyze their effects by determining probability of risk factors. Tran et al., (2003) incorporate the AHP technique with the expected maximum utility (EMU) to evaluate renewal priorities of irrigation assets grouped by types and location within the hydraulic system. Zahraie et al. (2005) used the AHP to rank the Regional Water Authorities (RWA's) performance based on a set of 97 criteria to quantify different aspects of water supply reliability and social, economic, and cultural effectiveness of the activities in the area of water resources development, planning, and management.

Al-Harbi, (2001) applied the Analytic Hierarchy Process AHP as a potential decision making method for use in project management. It has been applied to select the best contractors who are able to execute the project, based on prioritizing the different prequalification criteria, including experience, financial stability, quality performance, manpower resources, and equipment resources . Similarly, Mahdi et al. (2002) used the AHP method to develop a contractor screening model that was categorized into a number of predefined contractor criteria, including experience, financial stability, and past performance. Cheung et al. (2002) develop a decision-making model for dispute resolution strategy selection using the AHP and multi-attribute utility technique (MAUT). The model comprises four parts: selection criteria, dispute resolution strategies, collection of utility factors and selection criteria weightings. Al-Tabtabai et al, (2004), also, used the AHP method to quantify gains and losses for analyzing and resolving conflict in construction management. Gunhan et al, (2005) deployed the AHP and Delphi techniques for evaluating the importance of factors that affecting international construction projects. Al-Khalil, (2002) developed a model using the AHP to select the most appropriate project delivery method, including the design–bid–build (DBB) method, the design– bid (DB) method, and the construction management (CM) method. The ranking of the project delivery methods is based on several factors, including project characteristics, owner's needs, and owner's preferences. Zayed et al. (2004) integrated the AHP and fuzzy logic methods to develop a productivity index model for piling process. The authors developed the model based on ten selected qualitative productivity factors, which considered as the most important factors that affect piling productivity. Zhao et al., (2004) applied the AHP method to develop a simulation approach for evaluating the relative weighting of fire safety attributes of buildings.

II.7.3. The Analytical Hierarchy Process (AHP) Technique

Saaty, (1982) stated that solving problems analytically is based on three distinguished principles; (i) constructing hierarchies, (ii) establishing priorities, and (iii) logical consistency. So, several steps need to be followed to model a problem using the AHP method (Saaty, 1982; 1991). These steps are summarized in the following;

Step 1: Setting up the hierarchy

The first and important step in the AHP technique is to define the problem and develop a hierarchy, which will accurately represent the problem by breaking it down into its components, as shown in Figure II-18. The three major levels of the hierarchy are the goal, criteria/factors, and alternatives. The first level represents the overall goal of the decision-maker (expert). The second level consists of several different criteria/factors that contribute to the overall goal. The last level of the hierarchy then describes the alternatives which are to be evaluated in terms of the criteria in the second level.

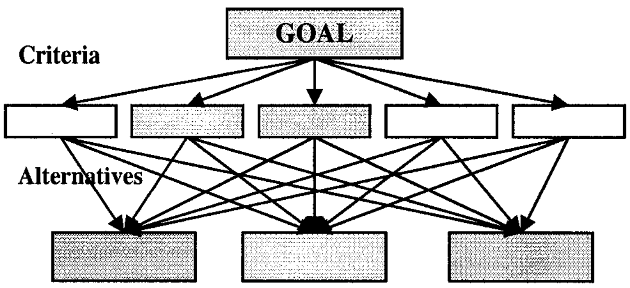

Figure II-18 A Three Level Hierarchy (Saaty, 1991)

Step 2: Pair-wise Comparison Matrices:

This step is concerned of developing relation within the structure through pair-wise comparison matrices (*size n x n*) that compare the criteria/factors with themselves. Pair-wise comparisons matrices are considered the basic of the AHP methodology. The pair-wise comparison matrix has several important characteristics as follows;

1. The diagonal elements are all equal to one, because they represent comparison of a criterion with itself.
2. The lower triangle elements are the reciprocal of the upper triangular elements (i.e. aij = 1/aji), as shown in Table II-6.
3. All numbers in the matrix are positive.

Table II-6 Pair-wise comparison matrix for different alternatives

Criteria/ Factors	a_1	a_2	a_3	a_4
a_1	1	a_{21}	a_{31}	a_{41}
a_2	a_{12}	1	a_{32}	a_{42}
a_3	a_{13}	a_{23}	1	a_{43}
a_4	a_{14}	a_{24}	a_{34}	1

Step 3: Assigning Priorities:

Then the matrix is filled in with numerical values representing the relative dominance, importance, preference, or likelihood, of one criteria/factor over another based on the common attribute they share in achieving the overall goal. A ratio of priorities can be established based on the scale of relative importance (1-9), as shown in Table II-7. This method is used in AHP allowing one to use both subjective and objective data in making pair-wise comparisons.

Table II-7 Pairwise Comparison Scale (Saaty, 2001)

Intensity of Importance	Definition	Explanation
1.0	Equal importance	Two activities contribute equally to the objective
2.0	Weak	Between Equal and Moderate
3.0	Moderate importance	Experience and judgment slightly favor one activity over another
4.0	Moderate plus	Between Moderate and Strong
5.0	Strong importance	Experience and judgment strongly favor one activity over another
6.0	Strong plus	Between Strong and Very strong
7.0	Very strong or demonstrated importance	An activity is favored very strongly over another; its dominance demonstrated in practice
8.0	Very, very strong	Between Very strong and Extreme
9.0	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation.

A high value indicates that the factor is relatively more important than the other factor at the top of the matrix. When a factor is compared with itself the ratio of importance is equal to (1.0), which will result in a diagonal line across the matrix.

Step 4: Establish Priority Vector:

In this step, the eigenvalue method of Saaty, (1982) is used for calculating the eigenvector or weighting vector for each pair-wise matrix. The decision-maker uses the numbers from the matrix (Eigenvalues) to get an overall priority weights for each criteria/factor. The priority weights are calculated as follows;

- First, the sum of the values are calculated in each column of the matrix (Reference to Table II-6);

$$\mathbf{A_1 = a_{11} + a_{12} + a_{13} + a_{14}}$$
$$\mathbf{A_2 = a_{21} + a_{22} + a_{23} + a_{24}}$$
$$\mathbf{A_3 = a_{31} + a_{32} + a_{33} + a_{34}}$$
$$\mathbf{A_4 = a_{41} + a_{42} + a_{43} + a_{44}}$$

- Then, the results are divided by its column sum for normalization;

$$\textbf{Norm. } \mathbf{A_1 = a_{11} / A_1 + a_{12} / A_1 + a_{13} / A_1 + a_{14} / A_1}$$
$$\textbf{Norm. } \mathbf{A_2 = a_{21} / A_2 + a_{22} / A_2 + a_{23} / A_2 + a_{24} / A_2}$$
$$\textbf{Norm. } \mathbf{A_3 = a_{31} / A_3 + a_{32} / A_3 + a_{33} / A_3 + a_{34} / A_3}$$
$$\textbf{Norm. } \mathbf{A_4 = a_{41} / A_4 + a_{42} / A_4 + a_{43} / A_4 + a_{44} / A_4}$$

- Finally, the results are summed in each row of the matrix and divided by number of rows (n).

$$\mathbf{W_{a1} = (a_{11} + a_{21} + a_{31} + a_{41}) / 4}$$
$$\mathbf{W_{a2} = (a_{12} + a_{22} + a_{32} + a_{42}) / 4}$$
$$\mathbf{W_{a3} = (a_{13} + a_{23} + a_{33} + a_{43}) / 4}$$
$$\mathbf{W_{a4} = (a_{14} + a_{24} + a_{34} + a_{44}) / 4}$$

$$\textbf{Total Weight} = \mathbf{\sum W_i = W_{a1} + W_{a2} + W_{a3} + W_{a4} = 1.0}$$

The final result provides the relative weights or preferences for each criteria/factor on a scale out of 1.0 points. Each factor weight represents the relative importance of this factor among the other factors.

Step 5: Logical Consistency:

In this step the decision-maker verifies the logical consistency of overall priority weights of the previous step, by calculating consistency ratio. The value of the consistency ratio should be equal or less than 10%. The consistency index (C.I) is defined as the degree of deviation from consistency (Saaty, 1982). (C.I) is calculated as follows:

$$\mathbf{C.I} = \frac{(\lambda_{max} - n)}{(n - 1)} \qquad \textbf{(II-1)}$$

Where,

n = the matrix size

λ_{max} = the maximum eigenvalue of the comparison matrix

Whereas the consistency ratio (C.R) is defined as the ratio of the consistency index (C.I), for a particular set of judgments, to the average consistency index (R.I) for random comparisons for a matrix of the same size from a 1 to 9 scale (Saaty, 1982), as shown in Table II-8. (C.R) is calculated as follows:

$$\mathbf{C.R} = \frac{\mathbf{(C.I)}}{\mathbf{(R.I)}} \qquad \textbf{(II-2)}$$

Where,

C.I = ratio of the consistency index

R.I = ratio of the average consistency index

Table II-8 Average Random Consistency (RI), (Saaty,)

Size of matrix (n)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Random consistency Index (R.I)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

If the consistency ratio (C.R) is less or equal 10%, that means the results are acceptable. But if the results are more than 10% that means that the results are inconsistent. And hence, the decision-maker have to repeat the weighting assignment process until a (C.R) of 10% or less is achieved.

The inconsistency occurs due to different common factors. The most common causes of inconsistency are categorized as follows:

1. *Typing errors:* It happens when the expert entering one or more wrong value for judgments into the pair-wise comparison matrices or when the inverse of the intended value is entered.
2. *Lack of information:* It happens when the expert has insufficient or no information about the factors being compared, then judgments will seem to be random, which will result in a high inconsistency ratio.
3. *Lack of curiosity or concentration during the judgment process:* It happens when the expert is not really interested in the decision, or become fatigued.

Step 6: Combining Priority Weights:

After verification of priority weights (W_i) for all matrices that are consistent. The decision-maker linearly combines the different priority matrices to find out the final overall ranking output, by applying a weight to each followed by a summation of the results to generate a final overall ranking value as follows;

$$\textbf{\textit{Overall Ranking Value}} = \sum_{i}^{n} W_i(V_i) \qquad \textbf{(II-3)}$$

Where,

W_i = weight of factor i

V_i = Weight of sub-factor i

It should be noted that Steps 2 to 5 are performed for all levels in the proposed hierarchy.

II.8. SUMMARY

Deterioration of water system is neither uniform nor identical. It varies based on various uncertain factors, which cause variations in the condition.

Based on the previous, current research proposes a data analysis models, using the ANN and the AHP approaches, which can be used as a pre-investigation tool before deciding to use the direct inspection methods because of their expenses.

CHAPTER III

STUDY METHODOLOGY

III.1. INTRODUCTION

The methodology of current research is illustrated in Figure III-1. Current research employs the following steps: ***literature review***, ***data collection, condition rating scale, (ANN) condition rating model, (AHP) condition rating model, web-based condition rating system, and conclusion and recommendation.*** A brief description of the intended methodology is provided below.

III.2. LITERATURE REVIEW

This part summarizes relevant literature and presents the literature in different sections. Section II-2 in chapter II includes literature review for types and characteristics of pipes being used in water networks including metallic pipes, concrete pipes, and poly pipes. This section also includes a review of pipes failure behavior based on their material.

Section II-3 illustrates time-dependant factors that contribute to pipe deterioration. It includes physical, environmental, and operational factors. These factors provide the basic terminology and framework for developing the condition rating models.

In addition, an extensive literature review for the available direct, destructive / non-destructive, and indirect techniques are presented in section II-4. The direct destructive / non-destructive techniques include visual, physical, ultrasonic spectrum, electromagnetic, and acoustic. The indirect indicators and statistical methods include analyzing available data based on four common types of problems that occur in water distribution systems: structural condition, hydraulic capacity, leakage, and water quality.

Section II-5, shows literature review for the existing condition rating and deterioration models. Finally, a detailed and extensive literature review for artificial neural network (ANN) and analytical hierarchy process (AHP) approaches is presented in section II-6 and section II-7 respectively.

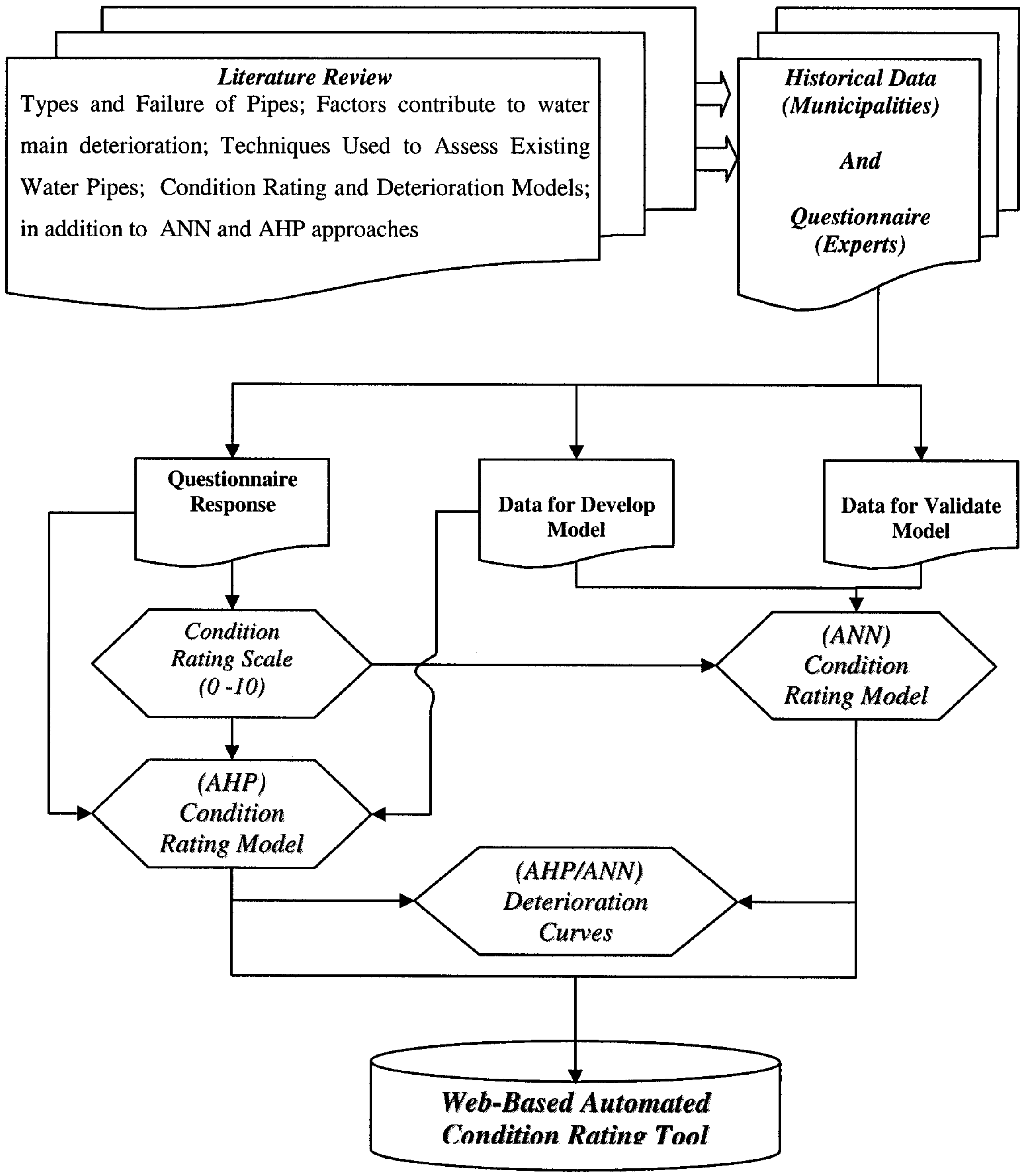

Figure III-1 Research Methodology

III.3. DATA COLLECTION

Data were collected from different municipalities in New Brunswick, Québec, and Ontario, Canada. Three data sets were received from municipalities: Moncton (New Brunswick); London (Ontario); and Longueiul (Québec). The collected data include type of pipes, year of installation, diameter, and number of breaks, type of soil, C-Factor, pipe depth and type of surface. Data were split randomly into two groups; one to develop the model and the other to verify it. The collected data was sufficient to verify and validate the developed models.

A questionnaire was sent to municipal experts and consultants in Canada and the United States. It collects the opinion of practitioners regarding the main factors affecting water mains condition and their sub-factors, and the condition rating scale. Their response includes pair-wise comparison matrices among main factors and all sub-factors inside each category; in addition to the suggested condition rating scale. Fifty questionnaires were sent to different experts and consultants. Twelve responses (24%) were received, which were incorporated to develop the global weight and priority of the deliberated factors, and the condition rating scale.

III.4. CONDITION RATING SCALE

A condition rating is proposed based on expert's decision and suggestions. The developed condition rating scale is divided into 6 categories ranging numerically from "0" to "10" and linguistically from "critical" to "Excellent". Each category is identified numerically and linguistically with its associated rehabilitation actions. It provides a framework for municipal engineer to decide and plan the required action in order to maintain their water mains (i.e. lining, cathodic protection, replacement).

III.5. The ANN CONDITION RATING MODEL

Supervised artificial neural network (ANN), using back propagation algorithm, is used to develop the required condition rating model based on several time-dependent factors. These factors provide the basic terminology and framework for modeling both condition rating and prediction models.

The framework of ANN application to condition rating problem passes through two phases: training and validation, as shown in Figure III-2. First, the physical, environmental, and operational factors, which are included in the model are identified and selected as shown and described in Table III-1.

Table III-1 Description of Factors included in (ANN) model

No.	Factor	Description of Factor
1	Type of Soil	Clay, Sand, Silt, Crushed Stone, etc.
2	Type of Road Surface	Asphalt, Seal, or Unpaved
3	Pipe Diameter	Internal diameter of pipe
4	Pipe Material	Type of pipe (Cast Iron, Ductile Iron, Asbestos)
5	Pipe Age	The age of laid pipe
6	Cover	Installation depth of a pipe
7	Breakage Rate	Number of pipe breaks/Km/year.
8	C-Factor	Hazen-William coefficient; Roughness factor

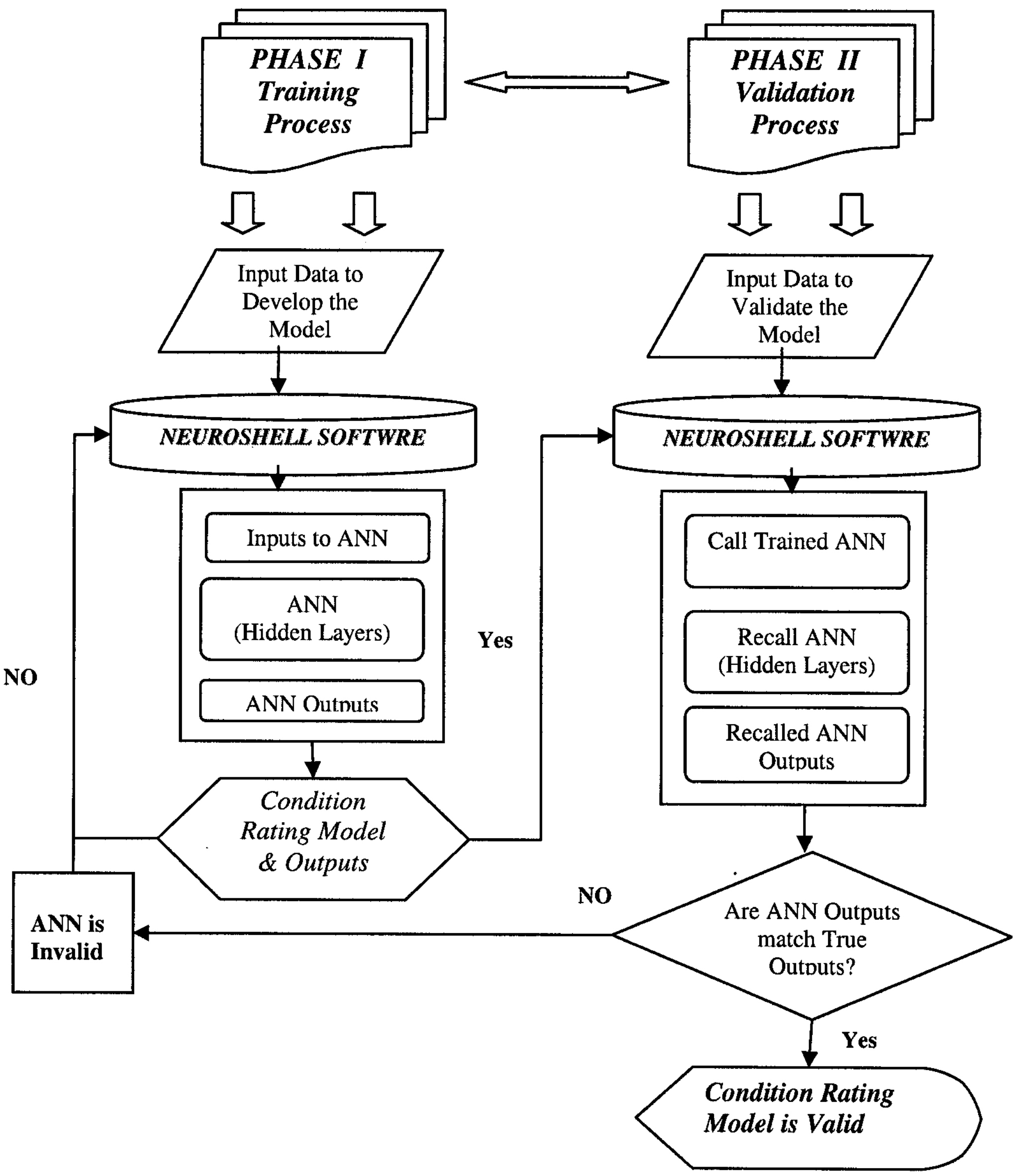

Figure III-2 The ANN Condition Rating Model Methodology Framework

Back-propagation neural network theory is employed to design the network architecture. Then, a neural network model is developed and trained based on the available data to assess water mains condition. However, some of these data will be used to investigate the practicality of the developed condition rating model, and to compare its performance with existing results. Finally, the accuracy of the developed neural network system is validated.

III.6. The AHP CONDITION RATING MODEL

The analytical hierarchy process (AHP) technique is used to develop a condition rating model to evaluate the sustainability of water mains when their conditions are unknown. The framework of AHP application to condition rating problem is shown in Figure III-3. First, a hierarchy of factors that contribute to water main deterioration is developed. The main factors (i.e. physical, environmental, and operational) that are included in the model are identified and shown in Table III-2.

Table III-2 Description of Factors Included in the Developed Model

No.	Factor	Description of Factor
1	Type of Soil	Clay, Sand, Silt, Alluvium, etc.
2	Type of Traffic/Road	Average daily traffic is High, Moderate, or Low; Type of road is Local, Primary, Secondary, or Highway
3	Type of Service	Residential, Commercial, Industrial, or Transmission
4	Ground Water Level	G.W.L is High, Moderate, or Low
5	Pipe Diameter	Internal diameter of pipe
6	Pipe Material	Type of pipe (Cast Iron, Ductile Iron, Steel, Asbestos, Concrete, PVC, Poly-ethylene)
7	Pipe Age	The age of laid pipe
8	Breakage Rate	Number of pipe breaks/Km/year.
9	C-Factor	Hazen-William coefficient; Roughness factor
10	Cathodic Protection	Cathodic protection is applied or not
11	Operational Pressure	Operational working pressure

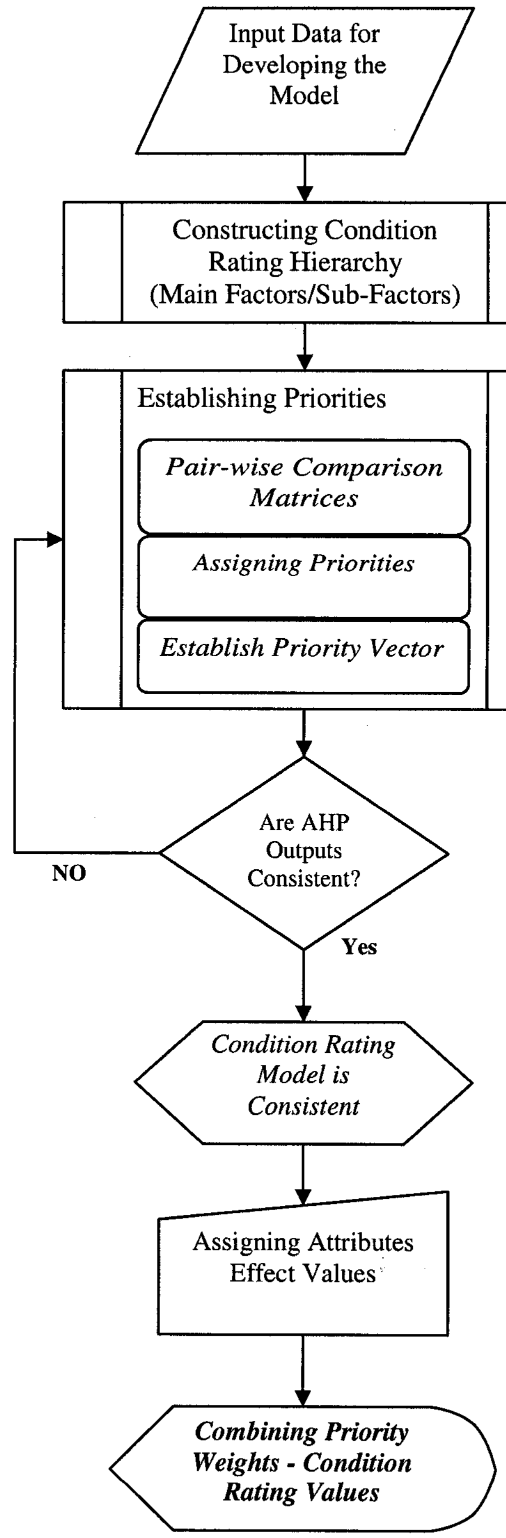

Figure III-3 AHPCondition Rating Model Methodology Framework

Thus, the factors' relative weights are obtained using a pair-wise comparison matrix of main factors and their sub-factors in each category. Each factor weight represents the relative importance of this factor among the other factors. Afterwards, the logical consistency of overall priority weights is verified based on the matrix consistency ratio (CR). If the CR is more than 10%, then the results are inconsistent. Hence, the assigned priority values should be modified until the CR value is verified. Finally, the overall weights are decomposed linearly to get the condition assessment value for each pattern in the data set (Saaty, 1982 & 1991).

III.7. DETERIORATION CURVES

Deterioration of water mains is considered an essential element that guides decision making in water main rehabilitation or renewal programs. Therefore, significant research effort has been carried out in the last two decades to model infrastructure deterioration.

In current research deterioration curves are developed based on the integration of the developed AHP/ANN condition rating models. These curves are done by building a relationship between the condition rating and age for each type of pipes (i.e. cast iron, and ductile iron pipes).

III.8. WEB-BASED AUTOMATED TOOL DESIGN

After building the condition rating models, a prototype web-based automated prediction tool (CR-Predictor) is developed using ASP.Net as programming language. It serves as a management system, which allows municipal expertise to predict the condition rating of the existing mains. The CR-Predictor is developed in away that allow users to integrate the AHP and ANN approaches based on their preferences.

In the AHP approach, the user firstly selects the main factors that would be included: Physical, environmental, and operational. Then, he/she identifies the sub-factors for each category based on a default list. Physical factors include pipe material, wall thickness, age, diameter, type of joints, thrust restraint, pipe lining and coating, dissimilar metals, pipe installation practices, and pipe depth. Environmental factors include pipe bedding, trench backfilling, soil type, service type, ground water level, frost penetration, pipe location, road type, average daily traffic, and disturbances practices. Operational factors cover breakage rate, Hazen-William coefficient, operational pressure, water quality, flow velocity, operation and maintenance practices, cathodic protection, service type, and fire hydrant existence.

After selecting the sub-factor in each category, the user proceeds to assign priority or importance values for the proposed pair-wise comparison matrices. Then, the CR-predictor calculates the weight of each sub-factor based on the assigned importance. Subsequently, the user assigns the effect value for each sub-factors' attributes. The attributes effect value is ranging between "0" and "10", and assigned based on municipal engineer experience. Finally, The CR-Predictor provides the condition rating value. The results are displayed in two different forms: (i) web-page browser and (ii) Excel file formats.

In the ANN approach, the CR-Predictor is linked to neural network executive program at the server (Neuroshell Predictor). So, if the user selects to use the ANN approach, he/she will be directed to that executive program. Afterwards, user will follow the instruction used by that program for training and testing (i.e. import historical data file, select input factors and output condition rating values). Then, the ANN model is saved to be used for condition rating prediction by importing and feeding input patterns into the trained network directly. The results are displayed on the screen web-browser and can be saved as Excel or Text files.

III.9. SUMMARY

The methodology of current research is presented. It includes the methodology of literature review, data collection, condition rating scale, ANN and AHP condition rating models, in addition to the development of CR-Predictor.

CHAPTER IV

CONDITION ASSESSMENT SCALE

IV.1. INTRODUCTION

There is no standard condition rating system (rating scale and its associated rehabilitation actions) for water mains in US and Canada until today. Only approximations and expert views are used to determine the condition, expected life, and rehabilitation actions for water mains. Best Practices (2003a) recommended and encouraged municipalities to standardize the condition rating of their underground assets and keep them in a database system. It also recommended converting all condition rating into a numerical scale or indices (i.e., 1 to 5, or 0 to 100 with the higher or lower number indicating an excellent condition). These indices and numerical scale can be used to predict the condition rating, track degradation over time, compare condition of different assets, and determine combined indices. Geem (2003) proposed a numeric scale from (0-1) for the pipe condition assessment using ANN. The lower value "0" indicates that the pipe is in excellent condition, whereas "1" value severe condition. Najafi and Kulandaivel (2005), also, proposed a numeric scale for evaluating the condition rating of sewer pipes. The numeric scale is ranging from (1-5), where "1" is the excellent condition, and "5" is the poor condition.

IV.2. PROPOSED CONDITION ASSESSMENT SCALE

Consequently, a questionnaire was designed and sent to different municipal experts and consultants, who are currently working in water system in the US and Canada

(Copy of the questionnaire is attached in Appendix (C)). It collected the best representation of condition rating scale, associated criteria, and suggested rehabilitation actions that should be applied to water mains at various conditions. The questionnaire suggested that the criteria could be "Excellent, Very Good, Good, Moderate, Bad, Poor, Critical, Very Bad or anything else suggested by the expert". In addition, it suggested that the actions could be "No action required at this time, Need flushing, Need inspection, Need lining, Rehabilitation required, Replacement needed, or any other suggestions". Table IV-1 shows the average collected results from these experts. Based upon the results of the questionnaire, the proposed condition rating scale is developed as shown in Figure IV-1.

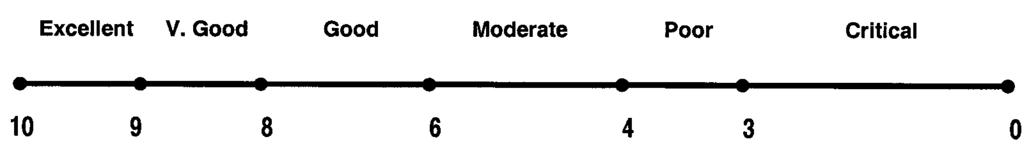

Figure IV-1 Proposed Condition Rating Scale

The developed condition rating scale provides a framework for municipal engineer to decide and plan the required action in order to maintain their water mains (i.e. lining, cathodic protection, replacement). For example, if it is reported that there is a significant signs of internal or external corrosion for a water main, or the remaining wall thickness is 50 to 75% of the original. Then, the condition of the water main is "Poor", and the municipal engineer should schedule for rehabilitation or replacement of this water main within the next 3-5 years.

Table IV-1 Numeric and Linguistic Scale for Condition Rating of Water Mains

Numeric Scale	Linguistic Scale	Criteria	Action
9 – 10	Excellent	Newly /Recently installed	No action required.
8 - 9	Very Good	Like new with no signs of corrosion or deterioration. Pipe wall thickness is even. BR ≤ 0.05	Re-assess in 15 years.
6 - 8	Good	Coatings, linings still in tact. Remaining wall thickness more than 90% of original.	Re-assess in 10 years. Schedule for Cathodic Protection within the next 5-10 years.
4 - 6	Moderate	Some damage to coatings and/or linings noted. Remaining wall thickness 75% or more of original.	Re-assess in 3-5 years. Schedule for lining and rehabilitation within the next 5-10 years.
3 - 4	Poor	No lining or coatings. Significant signs of internal or external corrosion. Remaining wall thickness 50 to 75% of original.	Schedule for rehabilitation or replacement within the next 3-5 years.
Less than 3	Critical	Severe internal or external corrosion. Remaining wall thickness less than 50% of original. BR >3.	Immediate repair or replacement required.

BR = Breakage Rate (Breaks/Km/Yr)

IV.3. SUMMARY

A condition rating scale is proposed to provide a framework for municipal engineer in order to plan the required rehabilitation actions for water mains. The developed scale is relevant to municipal engineers, consultants, and contractors in order to prioritize pipe inspection and rehabilitation planning for the existing water mains.

CHAPTER V

ARTIFICIAL NEURAL NETWORK APPLICATION TO CONDITION RATING MODELING

V.1. INTRODUCTION

Artificial Neural Network (ANN) technique can be used as a reliable methodology to assess the pipe condition without excavation (ASCE, 2000). This part presents a condition-rating model for evaluating the condition of water mains using the ANN technique. Current research considers different physical, environmental, and operational factors and their effect on different types of mains (i.e. Cast Iron, Ductile Iron, and Asbestos). The ANN input factors incorporate: pipe type, size, age, breakage rate, Hazen-Williams factor, excavation depth, soil type and top road surface; however, the output is pipe condition. The last section of this chapter presents an application example to validate the developed ANN model. The application example will demonstrate the capabilities of the developed system.

V.2. The ANN FRAMEWORK FOR CONDITION RATING

Supervised ANN, using the back propagation algorithm, is used to develop the required condition rating model. The framework of ANN application to condition rating problem passes through two phases: training phase and validation phase, as shown before in Figure III-2. In the training phase, EXCEL file sheet is imported and fed into NEUROSHELL-2 Software (Ward Systems Group Inc., Frederick, MD). Inputs and outputs are identified and selected. Qualitative variables are translated into numeric format (i.e. Type of pipes, Type of Soil, and Road Surface Type). The training input data is extracted randomly into training (85%) and testing data (15%). The training process uses "supervised learning" where the inputs and outputs are known within the context of the problem. Then, the BPNN architecture is designed, learned and tested. Several BPNN architectures were designed with the same input-output data to decide which network architecture best predict and solve the problem.

In the validation phase, data subset is fed into the trained ANN to generate outputs. These outputs are compared to the validation data outputs to check the ANN validity.

V.3. FACTORS INCLUDED IN THE ANN MODEL

Various physical, environmental, and operational factors affect the condition rating of water mains. Factors, which contribute to the model development, are identified and selected based on availability of historical data as shown in Figure V-1. However, other factors, which previously presented in Table II-3, can be included in future studies.

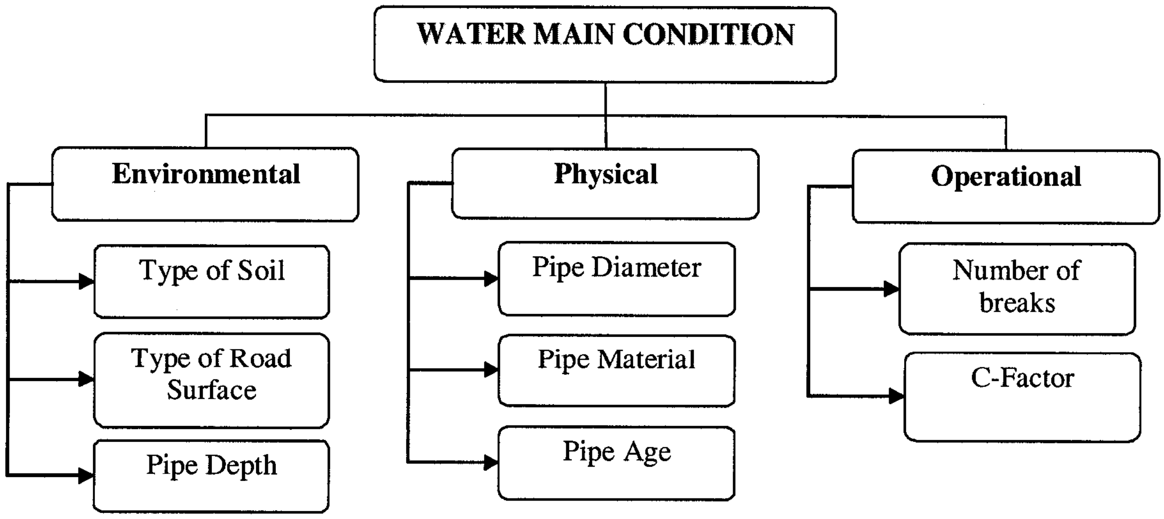

Figure V-1 Factors that Are Included in the Condition Rating Model of Water Mains

Environmental factors include type of soil, type of surface, and pipe cover (depth). Physical factors include pipe material, diameter, and age. Operational factors include number of breaks, and Hazen-William Coefficient (C-Factor), which is a measure of pipe wall roughness that slows down flow because of friction. The higher the (C-Factor) value, the smoother is the pipe (AWWA, 1989). The description of these factors is previously shown in Table III-1.

V.4. The ANN CONDITION RATING MODEL FOR WATER MAINS

The purpose of the condition rating is to objectively rate or scale the current condition of buried pipes based on the historical record. An ANN model is developed to rate or scale the current condition of water mains based on several physical, environmental, and operational factors. Eight input variables are identified and selected in current study, based on data availability, as shown in Figure V-2. Each variable is represented by one artificial neuron in the ANN input layer (eight neurons): type of pipe, age, size (diameter), rate of breakage, C-factor (Hazen-William factor), depth, type of road surface, and type of soil. Current study considers three categories of pipes: Asbestos, Cast Iron, and Ductile Iron (Based on collected Data- 1). Type of road surface consists of three categories: Asphalt, Seal, and Unpaved. Soil type includes eight categories: Organic Clay, Clay, Clay/Crushed stone, clay/sand, organic crushed stone, crushed stone, sand, and silt. The output variable includes one neuron: condition rating scale from "0" to "10". Therefore, the ANN output structure includes only one neuron in the output layer.

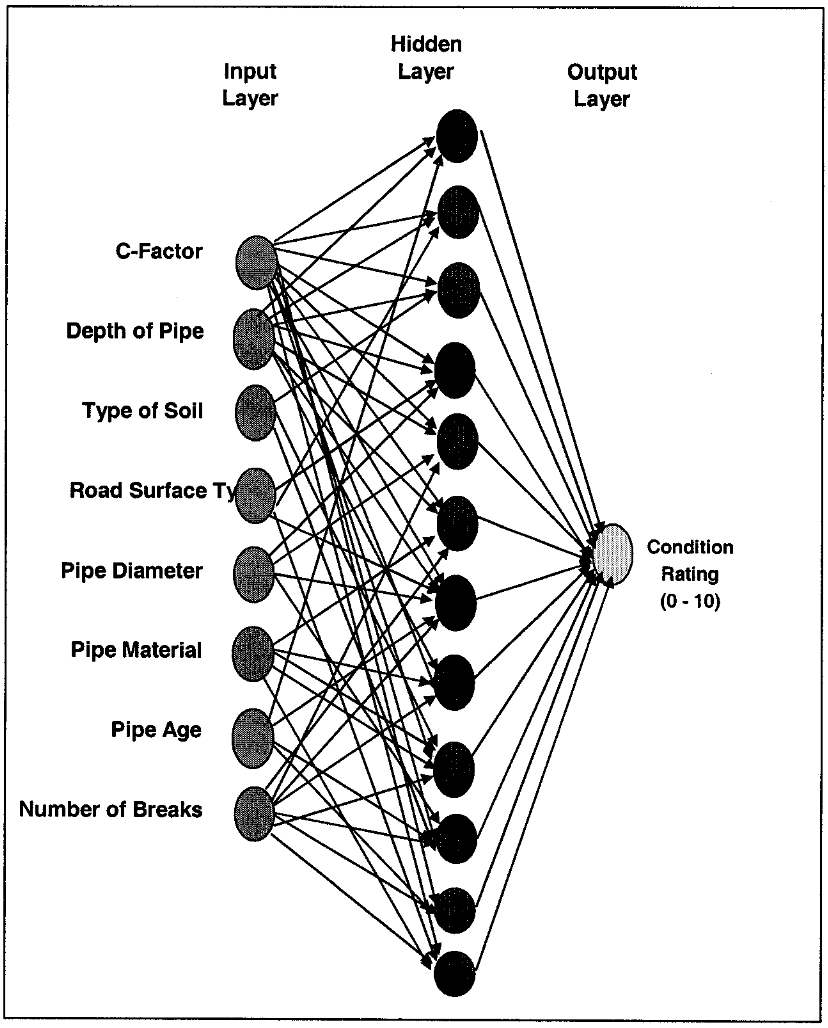

Figure V-2 Typical ANN Architecture for Condition Rating of Water Mains

NEUROSHELL-2 Software is used to develop the proposed (ANN) model. It has been used for several reasons; ease of use, speed of training, and use the most effective algorithm available including back-propagation with flexible user-optimization of training parameters. It also has different criteria for stopping network training, and different methods for handling missing data (Attalla et al., 2003). As described earlier, 500 training patterns are fed into the software. Then, the training input data is extracted randomly into 425 training patterns (85%) and 75 testing pattern (15%). The training process uses supervised back-propagation network architecture. The (ANN) learning rate is 0.005, the rate of which (ANN) will learn patterns in the training data set, and the number of learning events is 568400. Minimum average error in training is 0.00119, as shown in Figure V-3 and Figure V-4. In addition, minimum average error in testing is 0.00138. For further details regarding the (ANN) features, the reader is referred to Tsoukalas and Uhrig (1997).

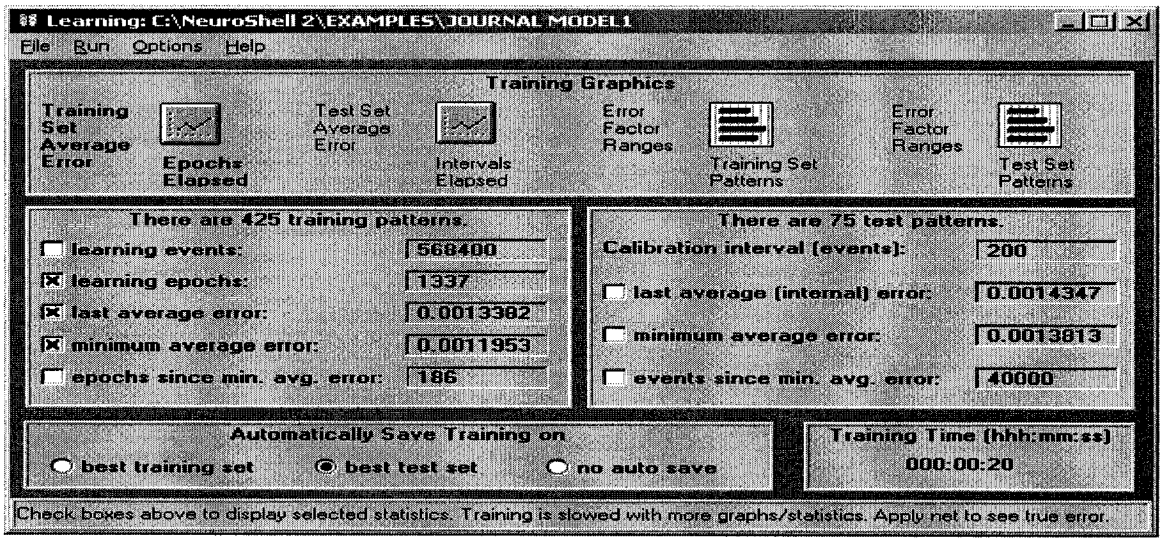

Figure V-3 Training and Testing Results

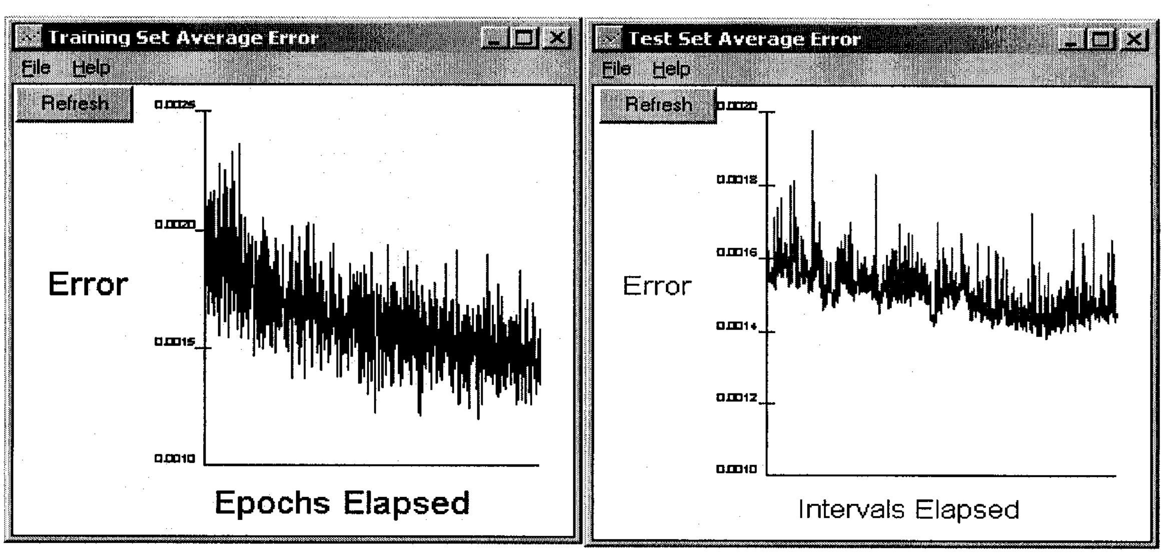

Figure V-4 Average Error for Training Set and Test Set of (ANN) Using NEUROSHELL

After training and testing the (ANN), results show the following;

- R-squared value is 0.9311,
- Mean squared error is 0.088,
- Mean absolute error is 0.232,
- Minimum absolute error is 0.0,
- Maximum absolute error is 1.036, and
- Correlation coefficient (r) is 0.9653.

It also shows that 70.6% of the outputs are within the 5% difference and 95.4% are within 10% difference, as shown in Figure V-5. Copy of the training and testing input and output schema are presented in Appendix "D".

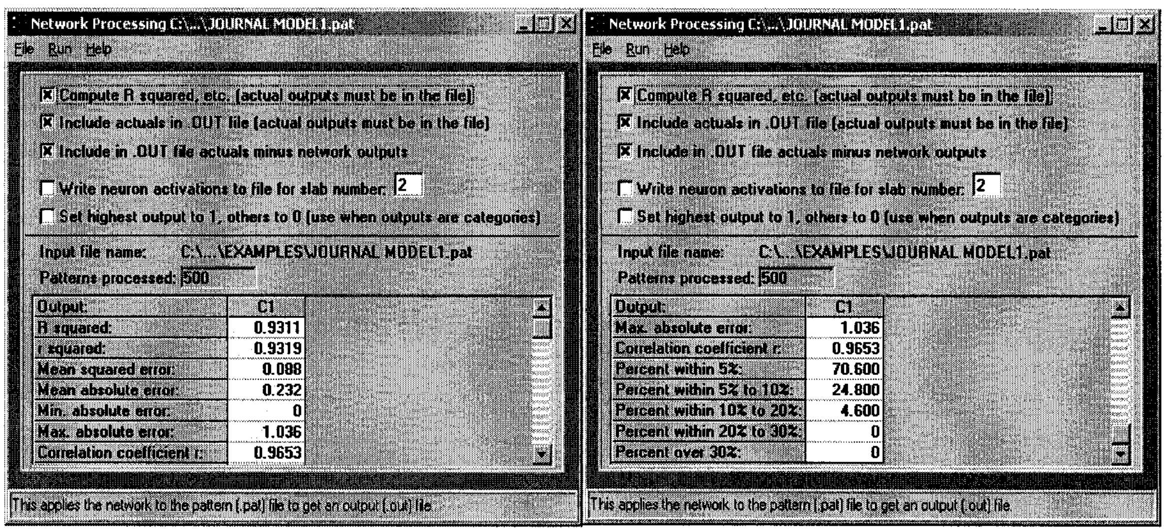

Figure V-5 Processing Neural Network Results

V.5. FACTORS WEIGHT

The NEUROSHELL-2 Software has the ability to determine contribution weights of input variables (i.e. pipe type, age, depth, etc) on the output variable (Condition

Rating) as shown in Figure V-6 and Table V-1. It is noticed that the most contributed factor to water mains condition is the breakage rate (30.17%); however, the second factor is age (13.56%). On the other hand, the least factor is type of surface (5.91%).

Table V-1 Factors Contribution Weight

No.	Factors	Weight	No.	Factors	Weight
1	Type of Pipe	0.12301	5	C-Factor	0.10132
2	Age	0.13557	6	Cover	0.07240
3	Size	0.11838	7	Type of Surface	0.05911
4	Breakage Rate	0.30166	8	Type of Soil	0.08855

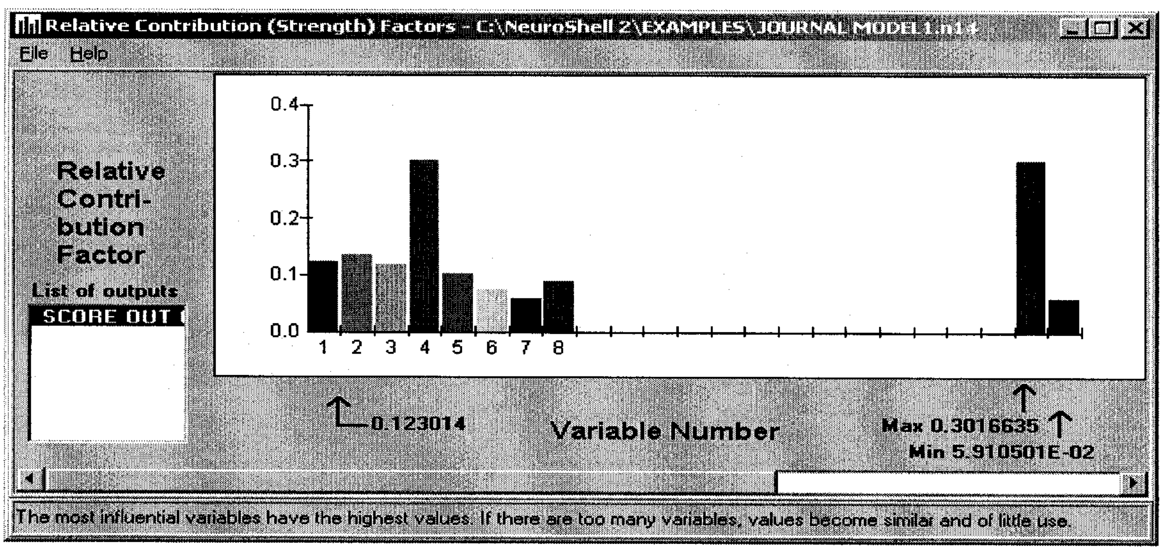

Figure V-6 Relative Contribution Input Factor Weights

V.6. The ANN MODEL VALIDATION

Based upon the above discussion, the ANN model is verified and prepared for validation. The validation data set is embedded into the model to compare its results with actual data. Based on Zayed and Halpin (2005), two equations (V-1) & (V-2) are used to validate the developed ANN model. Equation (2) represents the average validity percent (AVP), which shows the validation percent out of 100, and equation (V-1) represents the average invalidity percent (AIP), which shows the prediction error. The (AIP) and (AVP) values are determined as follows:

$$\boldsymbol{AIP = \left(\sum_{i=1}^{n} \left| 1-(E_i/C_i) \right| \right) / n} \qquad \textbf{(V-1)}$$

$$\boldsymbol{AVP = 1 - AIP} \qquad \textbf{(V-2)}$$

Where,

AIP = Average Invalidity Percent
AVP = Average Validity Percent
E_i = Estimated/Predicted Value
C_i = Actual Value

Dikmen et al. (2005) used three error terms to investigate the performance of their developed model. These terms are root mean square error (RMS), mean absolute error (MAE), and mean absolute percentage error (MAPE), as shown in the following equations (V-3), (V-4), and (V-5):

$$\boldsymbol{RMS = \frac{\sqrt{\sum_{i=1}^{n} (Actual_i - Predicted_i)^2}}{n}} \qquad \textbf{(V-3)}$$

$$MAE = \frac{\sum_{i=1}^{n} \left| Actual_i - Predicted_i \right|}{n} \qquad \textbf{(V-4)}$$

$$MAPE = \frac{\sum_{i=1}^{n} \left| Actual_i - Predicted_i \right| / Actual_i}{n} \times 100 \qquad \textbf{(V-5)}$$

It is noticed that (AIP), equation (V-1), is equivalent to (MAPE), equation (V-5); therefore, four equations ((V-1), (V-2), (V-3), and (V-4)) will be used to check the performance of the developed ANN model. Sixty validation data points are fed into the developed ANN model in order to get the predicted outputs. After applying the four equations, the results show that;

- AIP = 0.04261,
- AVP = 0.9574,
- RMS = 0.0451, and
- MAE = 0.2809.

Validation results are shown in appendix (D). In addition to above, results show that 71.7% of the outputs are within 5% difference, 91.7% are within 10% difference, and consequently, 100% are within 12.65% difference. The above results are fairly good and acceptable whereas Figure V-7 and Figure V-8 further clarify these results.

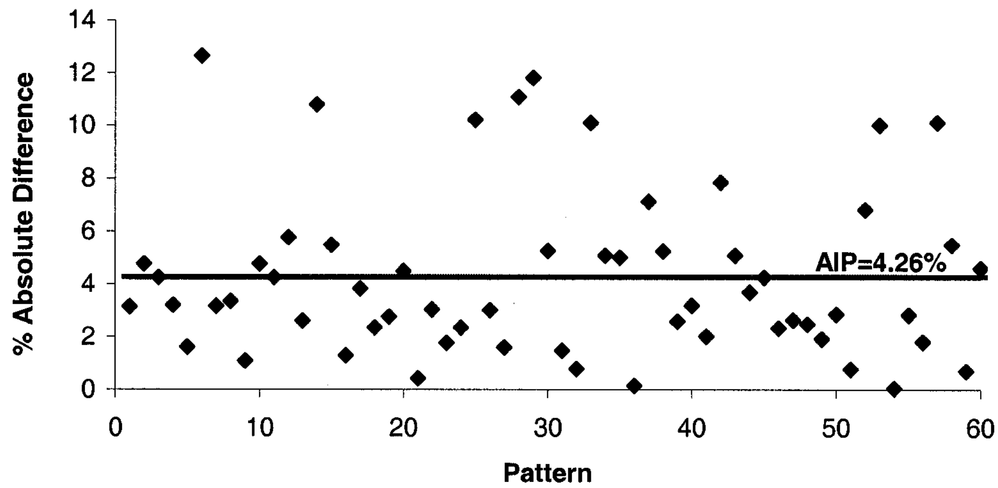

Figure V-7 Absolute Output Difference (Validation Chart)

Figure V-7 shows the calculation of absolute output difference using the (AIP) model in equation (V-1). It shows the scatter plot for the absolute difference points in which the maximum absolute difference is approximately 12.5% and the AIP is 4.26%.

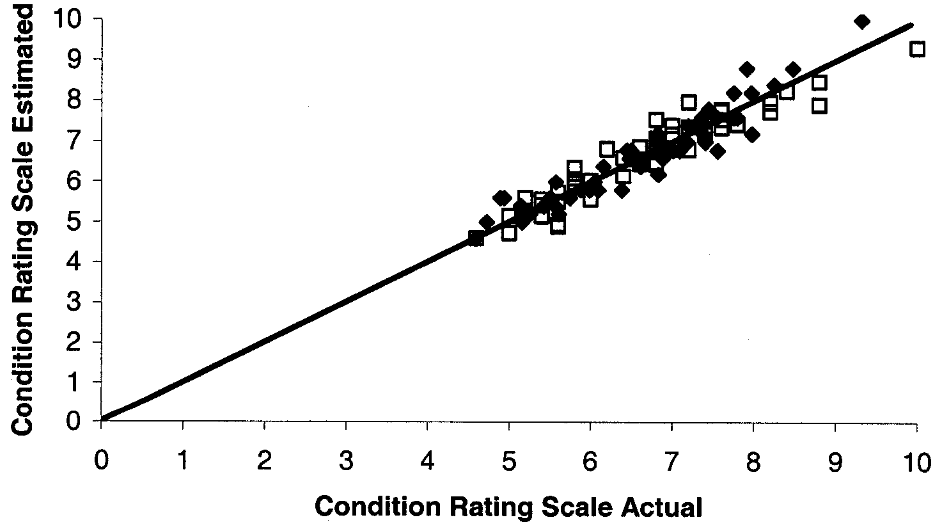

Figure V-8 Accuracy of the Proposed ANN in Forecasting Condition Rating

In addition, Figure V-8 shows the accuracy of the proposed model's prediction for condition rating when it is compared to actual values. Both figures show that the developed condition rating model is robust and capable to be used as a prediction tool.

V.7. PREDICTION CONDITION RATING MODELS FOR WATER MAINS

V.7.1. Asbestos Water Mains

Based on the developed ANN model, a relation between condition rating (CR) and breakage rate (BR) is done to predict the (CR) of a water main based on its breakage rate. Figure V-9 show a polynomial relation of third degree between the (BR) and (CR) of Asbestos pipes as follows:

$$\mathbf{BR = -0.1863\ CR^3 + 4.2578\ CR^2 - 32.338\ CR + 81.743\ (R^2 = 0.8447)} \qquad \mathbf{(V\text{-}6)}$$

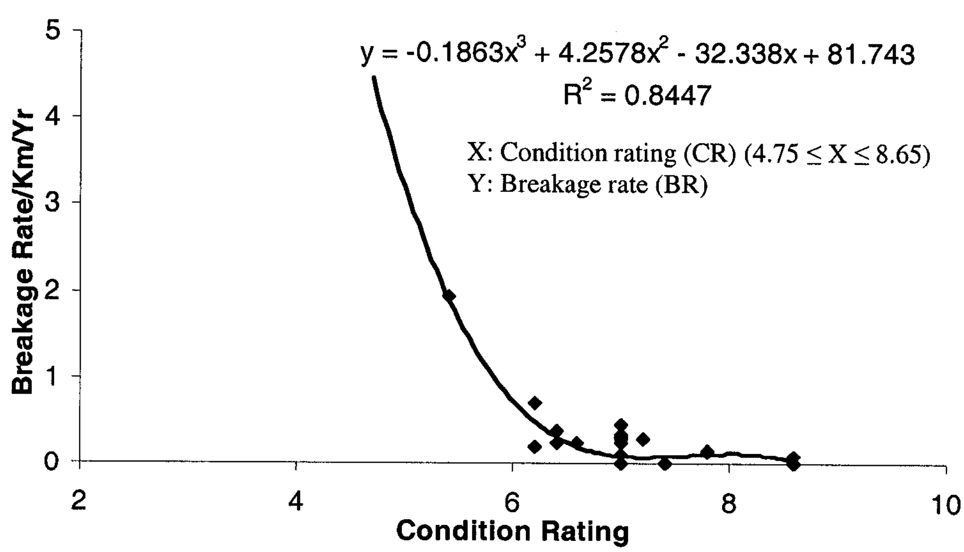

Figure V-9 Breakage Rate vs. Condition Rating for Asbestos Pipes

It shows an inverse relation between BR and CR within the following CR limits: $4.75 \leq CR \leq 8.65$.

Based on Figure V-9, if the breakage rate is known for a specified water main, municipal engineer can predict its condition rating. For example, if it is reported that the breakage rate for an Asbestos water main is 0.76, then, the condition rating is 6.0. This means, in reference to Table IV-1, that the Asbestos water main is in "Moderate" condition; hence, the municipal engineer has to schedule rehabilitation for such pipe within the next 5- 10 years, and re-assess it in the next 3-5 years.

V.7.2. Cast Iron Water Mains (General: Before & After World War II)

Many factors affect the CR, such as breakage rate, pipe type and manufacturing time (before World War II or after). The performance of Cast Iron water mains shows differences between the pipes, which were manufactured before and after World War II (WWII).

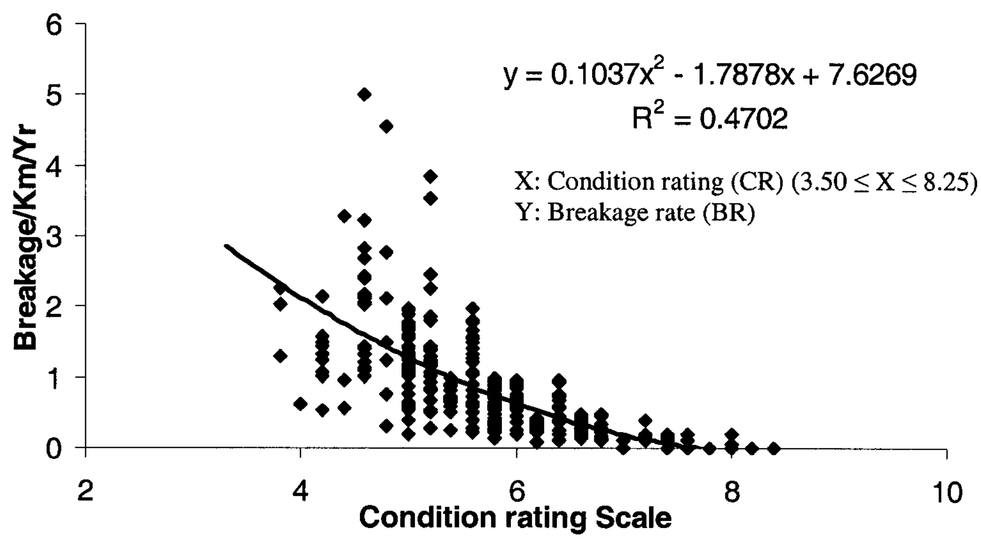

Figure V-10 Breakage Rate Vs. Condition Rating for Cast Iron (General: before and after WWII)

Figure V-10 shows a polynomial relation of second degree that represents the BR versus CR (general: before and after the WWII) of cast iron pipes as shown in equation (V-7) as follows:

BR = 0.1037CR² - 1.7878CR + 7.6269 (R² = 0.4702) **(V-7)**

$$BR = 0.1037CR^2 - 1.7878CR + 7.6269 \quad (R^2 = 0.4702) \tag{V-7}$$

It shows an inverse relation between BR and CR within the following CR limits: $3.50 \leq CR \leq 8.25$.

V.7.3. Cast Iron Water Mains after World War II

Figure V-11 shows a Polynomial relation of fourth degree that represents the BR versus CR of Cast Iron pipes manufactured after the WWII as shown in equation (V-8) as follows:

$$BR = -0.0089\,CR^4 + 0.1713CR^3 - 0.8835CR^2 - 0.8632CR + 12.085 \quad (R^2 = 0.6166) \tag{V-8}$$

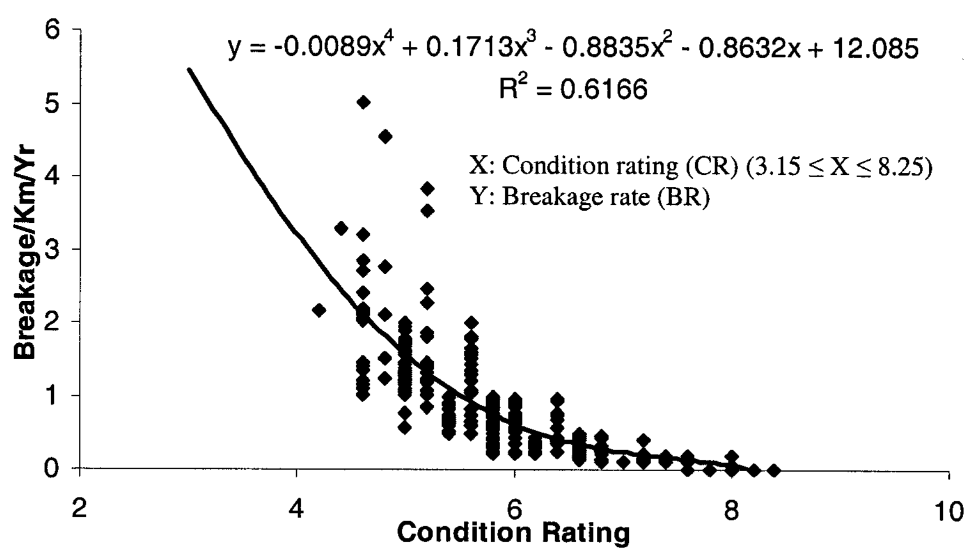

Figure V-11 Breakage Rate vs. Condition Rating for Cast Iron (After World War II)

It shows an inverse relation between BR and CR within the following CR limits: $3.15 \leq CR \leq 8.25$.

V.7.4. Cast Iron Water Mains before World War II

Figure V-12 shows a Polynomial relation of fourth degree that represents the BR versus CR of Cast Iron pipes manufactured before the WWII as shown in equation (V-9) as follows:

X: Condition rating (CR) $(3.15 \leq X \leq 8.25)$

Y: Breakage rate (BR)

$$\mathbf{BR = 0.0432\,CR^4 - 1.0433CR^3 + 9.4048CR^2 - 37.788CR + 57.781\ (R^2 = 0.7725)} \qquad \mathbf{(V\text{-}9)}$$

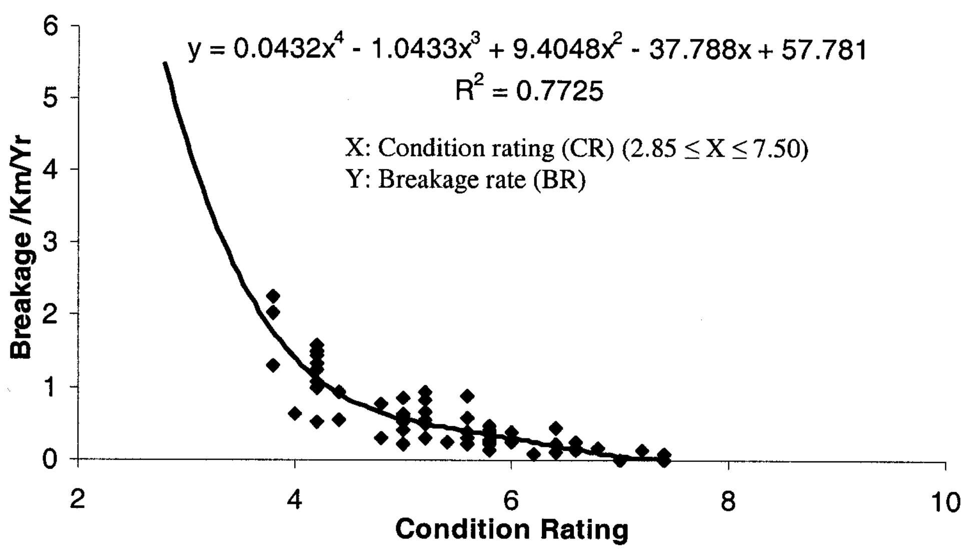

Figure V-12 Breakage Rate vs. Condition Rating for Cast Iron (Before World War II)

It shows an inverse relation between BR and CR within the following CR limits: $2.85 \leq CR \leq 7.50$.

In addition, Figure V-13 shows that the rate of breakage and failure for Cast Iron water mains after World War II is much greater than that before War. It is noticed that the breakage rate for these pipes, which were manufactured and installed before WWII, started almost after 6 decades, while those, which were manufactured and installed after WWII, started after 4 decades.

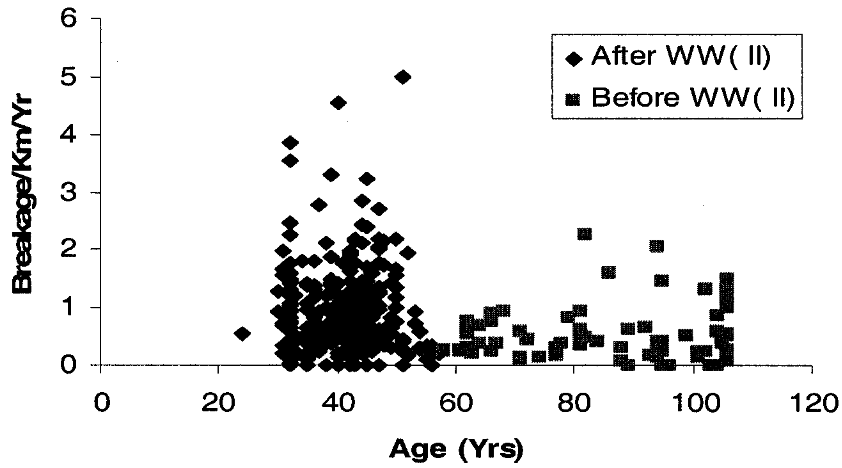

Figure V-13 Breakage Rate vs. Age for Cast Iron (Before & After World War II)

Diameter is one factor that might contribute to water main deterioration. The breakage rate (BR) of water mains decreased as the diameter (D) increased for Cast Iron pipes as shown in Figure V-14, which shows that the breakage rate of large pipe diameters is lower than small pipes. Usually, large diameters will be used for transmission mains; however, small ones will be used for distribution mains. In general, the breakage rate for distribution mains is higher than transmission mains for many reasons; pressure stability, fire hydrants services, operation and maintenance processes, cumulative tuberculation, and rehabilitation works for roads at several ages.

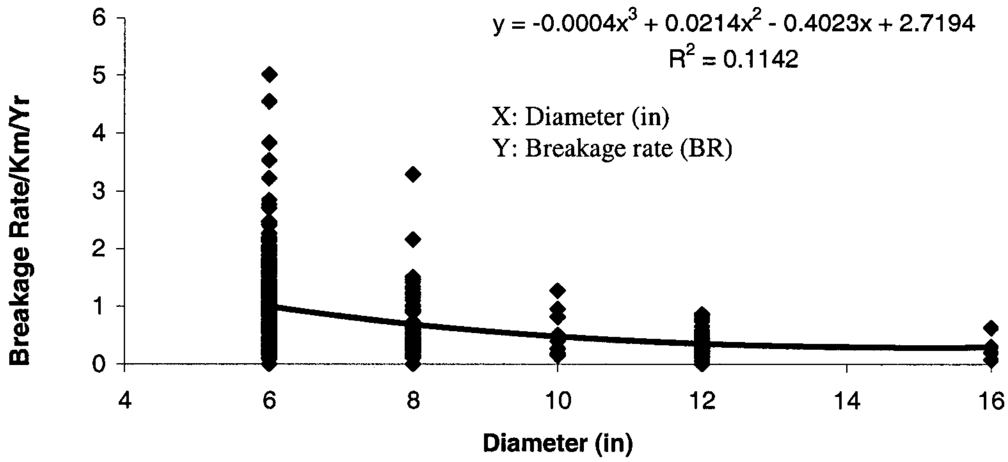

Figure V-14 Breakage Rate vs. Diameter for Cast Iron

V.7.5. Ductile Iron Water Mains

Figure V-15 shows a Polynomial relation of fourth degree for BR vs. CR of ductile iron pipes as shown in equation (V-10) as follows:

$$BR = -0.0053\,CR^4 + 0.1244CR^3 - 0.7882CR^2 - 0.4904CR + 12.723 \quad (R^2 = 0.6605) \qquad \text{(V-10)}$$

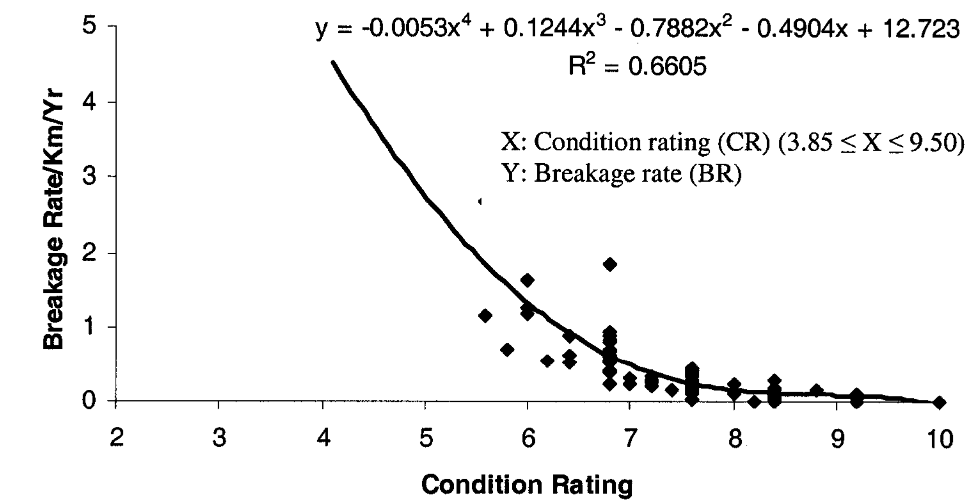

Figure V-15 Breakage Rate vs. Condition Rating for Ductile Iron

It shows an inverse relation between BR and CR within the limits: $3.85 \leq CA \leq 9.50$. It is also noticed from these figures that Ductile Iron pipes and Cast Iron pipes, which were manufactured and installed after WWII break and fail when the C-factor is relatively high. Whereas the Cast Iron pipes, which were manufactured before WWII, break and fail when C-factor is relatively low.

V.8. SUMMARY

An ANN model is developed to predict and assess the condition rating of water mains. Eight input factors that cover various physical, environmental, and operational conditions and one output factor (condition rating) are used to represent the condition rating process. Comparing the ANN model results to the validation data set outputs shows its robustness in predicting the water main condition rating for different pipe types (95.74%). The results show that 71.7% of the outputs are within the 5% difference, 91.7% are within 10% difference, and 100% are within 12.65% difference, which is fairly good and acceptable. Therefore, the proposed ANN model is robust and can be used to predict condition rating of water mains.

It is noticed that breakage rate has the highest effect on condition rating (30.20%); however, age comes in the second rank (13.60%). Results show an inverse relation between the condition rating (CA) and breakage rate (BR) for most water main types. It also shows differences between the performance of Cast Iron pipes before and after World War II.

CHAPTER VI

INTEGRATED AHP/ANN CONDITION RATING MODEL

VI.1. INTRODUCTION

This part presents a condition-rating model, which evaluates the sustainability of water mains using integrated Analytic Hierarchy Process (AHP) and artificial neural network (ANN). It incorporates physical, environmental, and operational factors, which include pipe type, size, age, breakage rate, Hazen-Williams factor, operational pressure, cathodic protection, ground water level, soil type, surface type, and road type. The factors' relative weights are obtained by calculating a pair-wise comparison matrix among main factors, and then among the sub-factors. The pair-wise comparison matrix is collected from experts. The result of this method provides relative weights of each factor on a scale out of 1.0. Weights represent the relative importance of this factor among other factors. The AHP technique is used for two reasons: (1) the effective ability of this technique to incorporate tangible and intangible factors, and (2) its ability of the AHP to break down the complex problem into small element through the hierarchal structure (Al-Khalil, 2002). The last section of this chapter presents an application example to test the developed AHP model. It demonstrates the capabilities of the developed system.

VI.2. APPLICATION OF AHP THEORY IN CONDITION RATING

The AHP model is developed to rate the current condition of water mains based on several physical, environmental, and operational factors. In order to apply the AHP technique, the problem passes through several steps as follows:

Step 1: Setting up the hierarchy

The water main condition problem is divided into four major levels as shown in Figure VI-1. Level 2 include 3 main factors (i.e. Environmental, Physical, and Operational); level 3 include 11 sub-factors (i.e. type of soil, ground water level, type of road/traffic, type of serviced area, pipe diameter, pipe Material, pipe age, number of breaks, C-factor (Roughness Factor), operational pressure, and Cathodic protection); and finally level 4 include the final outcome (condition assessment value ranging between (0-10). Description of the 11 sub-factors is presented before in Table III-2.

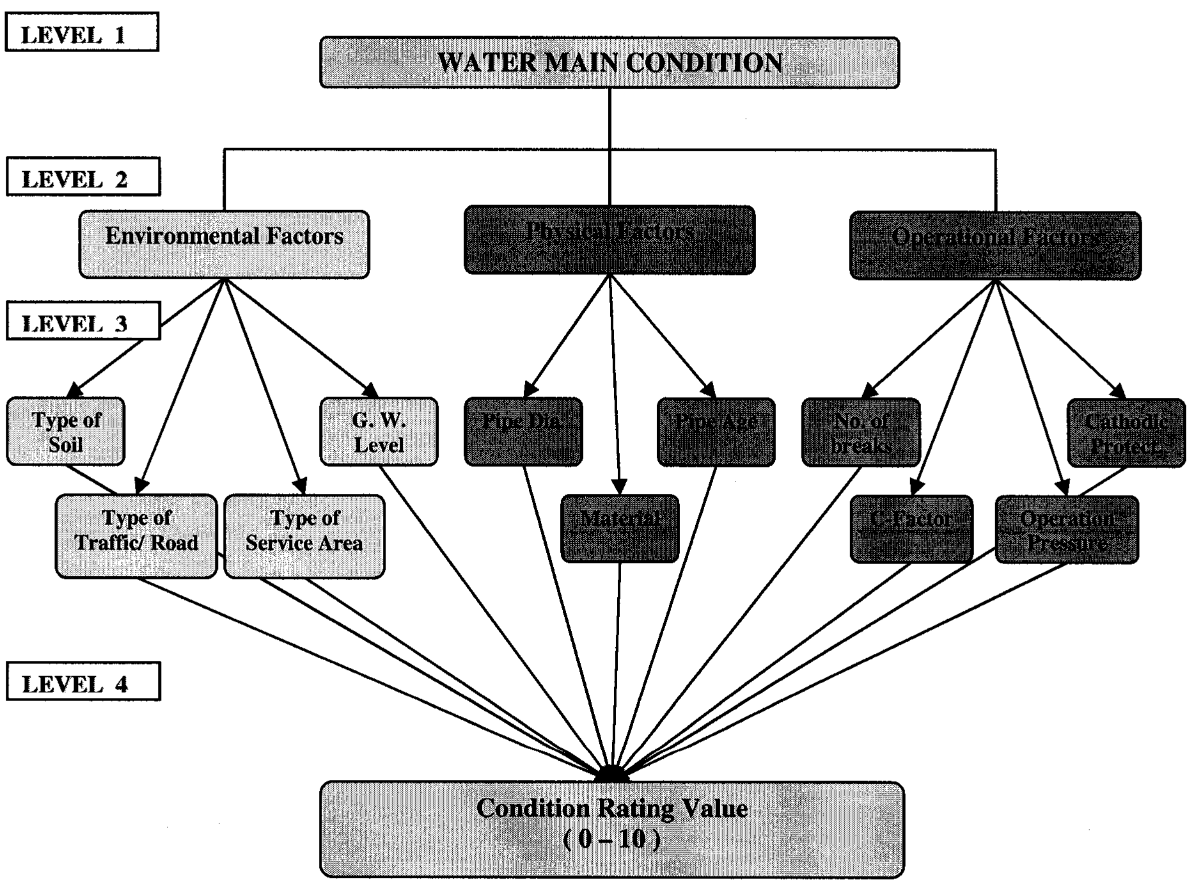

Figure VI-1 Hierarchy of the Developed Model

Step 2: Pair-wise Comparison Matrices:

In this step, a decision-maker develops the pair-wise comparison matrix for the 2nd Level, among main factors (Environmental, Physical, and Operational) and among the sub-factors in the 3rd Level.

Step 3: Assigning Priorities:

The AHP methodology is applied to these matrices in order to determine the weight of each factor. Consequently, all pair-wise comparison matrices, for main factors and sub-factors, are filled with numerical values (1-9) as shown in Table II-7, which represents the importance of each factor against the others. For example, Table VI-1, VI-2, VI-3, and VI-4, present the ratio of priorities completed by "Respondent No. 9".

Table VI-1 Main factors pair-wise comparison matrix (Respondent No. 9)

Factors	*Environmental*	*Physical*	*Operational*
Environmental	1	⅓	½
Physical	3	1	1.5
Operational	2	2/3	1

Table VI-2 Environmental' sub-factors pair-wise comparison matrix (Respondent No. 9)

Sub-Factors	*Type of Soil*	*Ground Water Level*	*Daily Traffic/ Type of Road*	*Type of Serviced Area*
Type of Soil	1	2	3	4
Ground Water Level	½	1	2	3
Daily Traffic/ Type of Road	⅓	½	1	2
Type of Serviced Area	¼	⅓	½	1

Table VI-3 Physical' sub-factors pair-wise comparison matrix (Respondent No. 9)

Sub- Factors	***Pipe Material***	***Pipe Diameter***	***Pipe Age***
Pipe Material	1	2	1
Pipe Diameter	½	1	½
Pipe Age	1	2	1

Table VI-4 Operational' sub-factors pair-wise comparison matrix (Respondent No. 9)

Sub-Factors	***No. of Breaks***	***Hazen-William Coefficient***	***Operational Pressure***	***Cathodic protection***
No. of Breaks	1	4	2	3
C-Factor	¼	1	½	⅓
Operational Pressure	½	2	1	2
Cathodic protection	⅓	3	½	1

A high value indicates that the factor on the left is relatively more important than the factor at the top. For example, it is noticed that "Respondent No. 9" assigned higher value, "3", for physical factors against environmental, "1", and operational factors, "2", which indicates that physical factors are 3 times as important as environmental factors, and 1.5 times as operational factors.

Step 4: Establish Priority Vector:

In this step, the eigenvector or weighting vector (W_i) for each pair-wise matrix, Table VI-1 to VI-4, is calculated using Saaty's methodology (1982). Each factor weight represents the relative importance of this factor among the other factors; however, the total value of these weights for each matrix is equal to one. Table VI-5 show these weights (W_i) in which physical factors has the highest priority and effect on water main condition (0.5390). On the other hand, environmental factor has the lowest effect of (0.1640). In addition, soil type has the highest weight inside the environmental factors (0.4658); pipe material score is also the highest in physical factor (0.40); and number of breaks is the highest in operational factor (0.4634).

Step 5: Logical Consistency:

This step is concerned with verification the logical consistency of overall priority weights using the consistency index (C.I) and consistency ratio (C.R). Table VI-5 shows the values of C.I and C.R for main factors and their sub-factors matrices.

Table VI-5 Weighting Vector; Consistency Index Ratio; and Consistency Ratio Values for each Pair-wise Matrix, (Table VI-1to Table VI-4), filled by "Respondent No. 9"

Factors	Weight (W_i)	C.I	C.R (%)
Main Factors (Table VI-1)			
Environmental	0.164	0.005	0.794
Physical	0.539		
Operational	0.297		
Environmental Factors (Table VI-2)			
Type of Soil	0.4658	0.016	1.724
Ground Water Level	0.2771		
Daily Traffic/ Type of Road	0.1611		
Type of Serviced Area	0.0960		
Physical Factors (Table VI-3)			
Pipe Material	0.40	0	0
Pipe Age	0.20		
Pipe Diameter	0.40		
Operational Factors (Table VI-4)			
Number of Breaks	0.4634	0.063	6.976
Hazen-William Coefficient	0.0995		
Operational Pressure	0.2514		
Cathodic Protection	0.1857		

It also shows that the C.I for the main matrix is 0.0050; however, the C.R value is 0.0079, which is less than 0.10. It means that the main matrix is consistent and the weight vector, which is generated from this matrix, is accepted. Similarly, the other matrices have C.R values of 0.017, 0.00, and 0.069, which are accepted too. All the matrices that are received from practitioners were consistent.

However, if the results are inconsistent, then the decision-maker should revise and improve matrix values until a C.R of 10% or less is achieved. The final results of weighting vector (W_i) for the ten respondents are shown in Table VI-6.

Table VI-6 Importance weighting vector values results (*Wi*) for all respondents

Factors	Response 1	Response 2	Response 3	Response 4	Response 5	Response 6	Response 7	Response 8	Response 9	Response 10
Physical Factor	**0.5**	**0.5**	**0.5455**	**0.3334**	**0.5**	**0.6**	**0.4286**	**0.4286**	**0.5389**	**0.5**
Pipe Material	0.2286	0.2307	0.5	0.3333	0.2	0.25	0.3333	0.6	0.4	0.5389
Pipe Diameter	0.0857	0.077	0.3333	0	0.4	0.25	0.3333	0.2	0.2	0.1638
Pipe Age	0.6857	0.6923	0.1667	0.6667	0.4	0.5	0.3334	0.2	0.4	0.2973
Environmental Factors	**0.1667**	**0.1667**	**0.2727**	**0.3333**	**0.1667**	**0.3**	**0.1428**	**0.1428**	**0.1638**	**0.1667**
Type of Soil	0.4286	0.48	0.4	0.6667	0.5455	0.3333	0.4547	0.4615	0.4658	0.3037
Ground Water Level	0.2143	0.16	0.2	0.3333	0.0909	0.3333	0.2631	0.1539	0.2771	0.232
Daily Traffic/ Type of Road	0.2143	0.12	0.2	0	0.1818	0.1667	0.1411	0.1539	0.1611	0.3576
Type of Serviced Area	0.1428	0.24	0.2	0	0.1818	0.1667	0.1411	0.2307	0.096	0.1067
Operational Factors	**0.3333**	**0.3333**	**0.1818**	**0.3333**	**0.3333**	**0.1**	**0.4286**	**0.4286**	**0.2973**	**0.3333**
No. of Breaks	0.3636	0.3871	0.2857	0.5	0.5455	0.126	0.4	0.4286	0.4634	0.4721
Hazen-William Coefficient	0.091	0.0968	0.2857	0	0.0909	0.2798	0.2	0.1428	0.0995	0.1192
Operational Pressure	0.1818	0.129	0.1429	0.1667	0.1818	0.3422	0.2	0.2143	0.2514	0.2516
Cathodic protection	0.3636	0.3871	0.2857	0.3333	0.1818	0.252	0.2	0.2143	0.1857	0.1571

Step 6: Decomposed Priority Weights:

After verifying the consistency of all matrices weights (W_i) are considered. Thus, the decomposed weight of each sub-factor will be calculated by multiplying the main factor weight by its sub-factor weight. This decomposed weight will represent the overall weight of such sub-factor. Accordingly, priority can be established based on this overall weight as shown in equation (VI-1) as follows:

Overall Sub-factor Decomposed Weight (SDWij) = Wi * (Vij) **(VI-1)**

Where:

Wi = Weight of factor i

Vij = Weight of sub-factor j within the factor i

Based on the "Respondent No. 9" results shown in Table VI-5 and equation (VI-1), the overall ranking values for sub-factors would be as follows;

Table VI-7 Subfactor Decomposed Weight

Sub-Factor	W_i	V_{ij}	SDW_{ij}
Type of Soil	0.164	0.4658	***0.0763***
Ground Water Level	0.164	0.2771	***0.0454***
Daily Traffic/ Type of Road	0.164	0.1611	***0.0264***
Type of Serviced Area	0.164	0.0960	***0.0157***
Pipe Material	0.539	0.4	***0.2156***
Pipe Age	0.539	0.2	***0.2156***
Pipe Diameter	0.539	0.4	***0.1078***
Number of Breaks	0.297	0.4634	***0.1378***
Hazen-William Coefficient	0.297	0.0995	***0.0296***
Operational Pressure	0.297	0.2514	***0.0747***
Cathodic Protection	0.297	0.1857	***0.0552***

Table VI-8 Total Importance Weightings Assessment by Respondents

Factors	Response 1	Response 2	Response 3	Response 4	Response 5	Response 6	Response 7	Response 8	Response 9	Response 10	W_i Average
Physical Factor											**0.4875**
Pipe Material	0.1143	0.1154	0.2728	0.1111	0.1000	0.1500	0.1429	0.2572	0.2156	0.2695	**0.1749**
Pipe Diameter	0.0429	0.0385	0.1818	0.0000	0.2000	0.1500	0.1429	0.0857	0.1078	0.0819	**0.1031**
Pipe Age	0.3429	0.3462	0.0909	0.2223	0.2000	0.3000	0.1429	0.0857	0.2156	0.1487	**0.2095**
Environmental Factors											**0.2022**
Type of Soil	0.0714	0.0800	0.1091	0.2222	0.0909	0.1000	0.0649	0.0659	0.0763	0.0506	**0.0931**
Ground Water Level	0.0357	0.0267	0.0545	0.1111	0.0152	0.1000	0.0376	0.0220	0.0454	0.0387	**0.0487**
Daily Traffic/ Type of Road	0.0357	0.0200	0.0545	0.0000	0.0303	0.0500	0.0201	0.0220	0.0264	0.0596	**0.0319**
Type of Serviced Area	0.0238	0.0400	0.0545	0.0000	0.0303	0.0500	0.0201	0.0329	0.0157	0.0178	**0.0285**
Operational Factors											**0.3103**
No. of Breaks	0.1212	0.1290	0.0519	0.1667	0.1818	0.0126	0.1714	0.1837	0.1378	0.1574	**0.1313**
Hazen-William Coefficient	0.0303	0.0323	0.0519	0.0000	0.0303	0.0280	0.0857	0.0612	0.0296	0.0397	**0.0389**
Operational Pressure	0.0606	0.0430	0.0260	0.0556	0.0606	0.0342	0.0857	0.0918	0.0747	0.0839	**0.0616**
Cathodic protection	0.1212	0.1290	0.0519	0.1111	0.0606	0.0252	0.0857	0.0918	0.0552	0.0524	**0.0784**

Consequently, the average values of main factors and sub-factors are calculated as shown in Table VI-8. It is noticed that physical factors contributes in condition assessment of water mains with contributes (49%), then, operational factor with (31%), and finally environmental factor with (20%), as shown in Figure VI 2. This shows the necessity of physical and operational factors and their sub-factors in condition rating assessment of water mains.

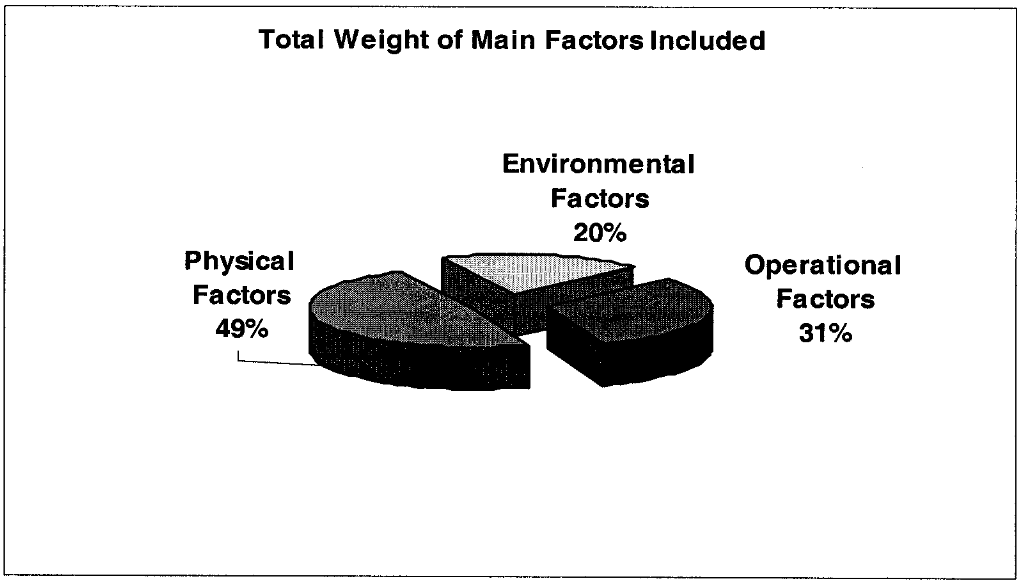

Figure VI-2 Total contribution weights of main factors in condition rating assessment

Table VI-8 shows that the highest contributed sub-factor to water main condition is pipe age (physical-20.95%); then, pipe material (physical-17.49%); however, the third factor is breakage rate (operational-13.13%). On the other hand, the least factor is type of service (environmental-2.85%), as shown in Figure VI-3.

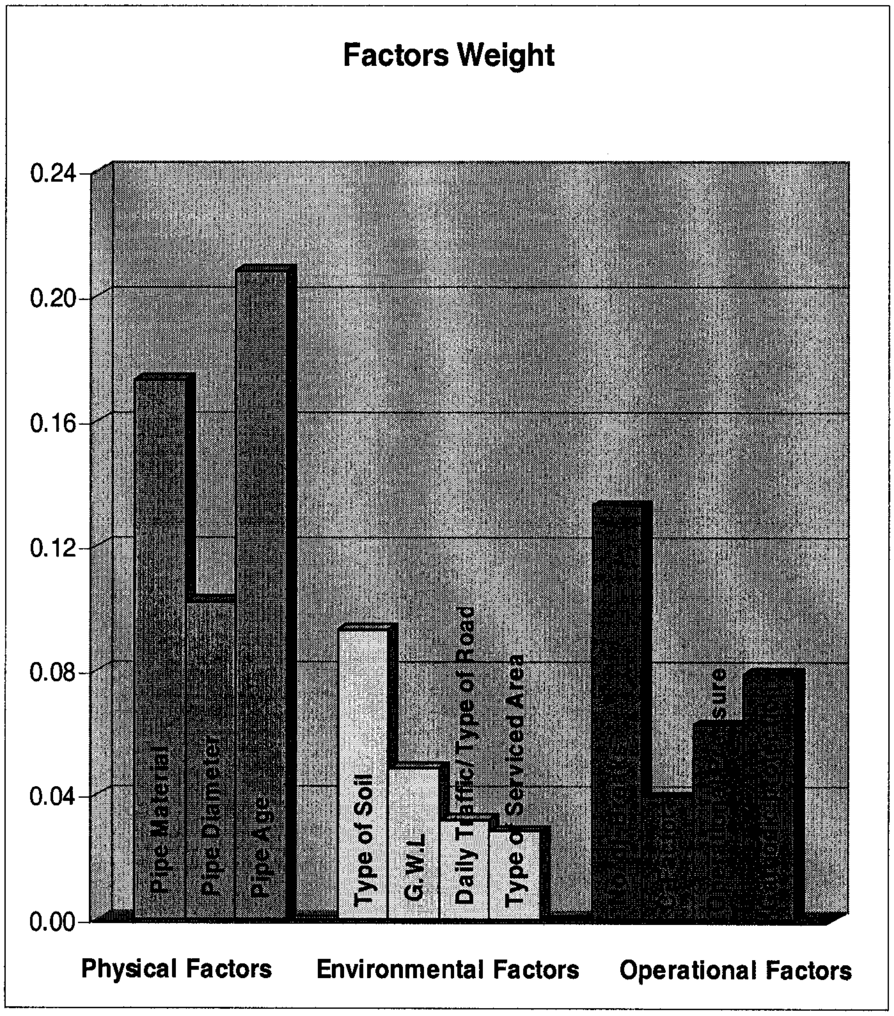

Figure VI-3 Total contribution weights of sub-factors in condition rating assessment

Step 7: Attributes Effect (AE_{ij}):

The decomposed weights represent a generic weight for factors and sub-factors. However, each sub-factor has various attributes in which they are not similar in their effect on water main condition. For example, pipe type sub-factor has various attributes, such as cast iron, steel, ductile iron, concrete, etc. These attributes do not have the same effect on water main condition. In addition, their performance is different from one municipality to the other. Therefore, the effect of such attributes to water main condition is considered through the attributes effect term (AE_{ij}).

Table VI-9 Average Attributes Effect Value (AE_{ij}) for Sub-factors criteria's

Factors	Average AE_{ij}	Factors	Average AE_{ij}
1. Physical Factors		**2.4** ***Average Daily Traffic***	
1.1 ***Type of Pipe***		• Heavy	6
• Cast Iron (Before WW)	8	• Moderate	8
• Cast Iron (Installed After WW)	6	• Low	10
• Ductile Iron	8		
• Asbestos	6	**2.5** ***Type of Road***	
• Concrete Pipes	7	• Local	8
• P.V.C	9	• Primary	6
• Polyethylene Pipes	10	• Secondary	10
		• Free way	5
1.2 ***Pipe Diameter***		• Arterial	5
• Less or equal 100mm	5		
• 150, and 200mm	7	**2.6** ***Type of Surface***	
• 250, and 300mm	8	• Asphalt	5
• 350, 400, and 450mm	9	• Seal	8
• Greater or equal 500mm	10	• Foot path	8
		• Unpaved	10
1.3 ***Pipe Age***			
• Greater than 90 yrs	0	**3. Operational Factors**	
• 90 yrs $\geq$ Age $\geq$ 80 yrs	1	**3.1** ***Number of Break***	
• 80 yrs $\geq$ Age $\geq$ 70 yrs	2	• Greater than 2 Breaks/km/yr	0
• 70 yrs $\geq$ Age $\geq$ 60 yrs	3	• $2.0 \geq BR \geq 1.0$	1
• 60 yrs $\geq$ Age $\geq$ 40 yrs	5	• $1.0 \geq BR \geq 0.5$	2
• 40 yrs $\geq$ Age $\geq$ 30 yrs	7	• $0.5 \geq BR \geq 0.2$	4
• 30 yrs $\geq$ Age $\geq$ 20 yrs	8	• $0.2 \geq BR \geq 0.1$	6
• 20 yrs $\geq$ Age $\geq$ 10 yrs	9	• $0.1 \geq BR \geq 0.0$	8
• Less than 10 yrs	10	• Less than 0.05 Brks/km/yr	10
2. Environmental Factors		**3.2** ***Hazen-William Coefficient***	
2.1 ***Type of Soil***		• Greater than 101	10
• Highly aggressive	0	• 101 $\geq$ C-Factor $\geq$ 81	8
• Aggressive	5	• 81 $\geq$ C-Factor $\geq$ 61	6
• Moderate	7	• 61 $\geq$ C-Factor $\geq$ 41	4
• Non-Aggressive	10	• Less than 41	2
2.2 ***Ground Water Level***			
• High	3	**3.3** ***Cathodic Protection***	
• Moderate	7	• Cathodic Protect. Applied	10
• Low	10	• Cathodic Protect. NOT Applied	6
2.3 ***Type of Service***	10	**3.4** ***Operational Pressure***	
• Industrial	8	• High	7
• Commercial	8	• Moderate	10
• Residential	10	• Low	10
• Rural (Transmission)			

AE_{ij} = Attribute Effect Value, BR= Breakage Rate (Breaks/Km/year)

Practitioners are required to assign the AE_{ij} for each sub-factor using a scale from 0 to 10 where "0" value represents the lowest effect and "10" represents the highest effect. Table VI-9 shows the average attribute effect for all sub-factors based on the proposed scale.

Step 8: Condition Assessment:

The last step in the AHP model is to obtain the overall condition assessment value on a scale of (0-10) using equation, by mathematically combining the different priority matrices with the attribute effect value for each criterion. The overall sub-factor ranking importance weights were calculated against each other as shown in step-6 and the criteria rankings in accordance with the attribute effect values is assigned in step-7. That is done by mathematically combining the different priority matrices with the efficiency rating score for each criterion followed by a summation of the results to generate a condition assessment value as follows:

$$\textit{Condition Rating (CR)} = \sum_{i=1}^{n} \sum_{j=1}^{m} (SDWij) * (AEij) \qquad \textbf{(VI-2)}$$

Where,

n = number of factors i

m = number of sub-factors j within the main factor i

$SDWij$ = Overall Sub-factor Decomposed Weight

$AEij$ = Attributes Effect Value of sub-factor j within the factor i,

Then,

$$\textit{Condition Rating (CR)} = \sum_{i=1}^{n} \sum_{j=1}^{m} Wi * Vij * AEij \qquad \textbf{(VI-3)}$$

Where,

Wi = Weight of factor i

V_{ij} = Weight of sub-factor j within the factor i

Based on the developed model, equation (VI-3), condition assessment of water mains can be determined for various pipe types.

VI.3. THE AHP MODEL APPLICATION

Based on the developed model, equation (VI-3), condition rating of water mains can be calculated for the available data sets based on the modified overall sub-factors weights and the average attributes effect values, Table VI-9. A sample of condition assessment results for the two data sets, data-1 (which represent one municipality) and data-2 (which represents other municipality), are shown in Table VI-10 and Table VI-11 respectively. According to the final result of the condition Rating (CR), municipal engineer can decide and plan the required action in order to maintain their water mains (i.e lining, cathodic protection, replacement). For example, it is reported (Table VI-10) that the condition assessment for the 12" cast iron pipe installed in 1895 is 3.5, which is in "Poor" conditions as the condition scale assesses. Hence, the municipal engineer should schedule for rehabilitation or replacement of that water main within the next 3-5 years (Reference to Table IV-1).

Table VI-10 A Sample of Condition Assessment Results for Data-1

PIPE_TYPE	YEAR INSTALLED	Age	SIZE (inch)	Breaks/km/yr	C-Factor	SURFACE	SOIL	Pipe Type (AE_{ij})	Age (AE_{ij})	Size (AE_{ij})	Break (AE_{ij})	C-Factor (AE_{ij})	Surface Type (AE_{ij})	Soil Type (AE_{ij})	Condition Rating	Linguistic Condition
ASBESTOS	1955	46	6	1.94	70	ASPHALT	CLAY	6	5	7	1	6	5	5	4.5	MODERATE
DUCTILE IRON	1974	27	6	0.11	89	ASPHALT	CRUSHED STONE	8	8	7	6	8	5	10	7.6	GOOD
DUCTILE IRON	1972	29	6	0.36	87	ASPHALT	CRUSHED STONE	8	8	7	4	8	5	10	7.1	GOOD
ASBESTOS	1958	43	20	0.00	73	ASPHALT	CLAY	6	5	10	10	6	5	5	7.0	GOOD
CAST IRON	1895	106	6	0.55	10	ASPHALT	CLAY	8	0	7	2	2	5	5	3.7	POOR
CAST IRON	1895	106	4	1.50	10	ASPHALT	CLAY	8	0	5	1	2	5	5	3.3	POOR
ASBESTOS	1953	48	20	0.00	68	ASPHALT	CLAY	6	5	10	10	6	5	5	7.0	GOOD
CAST IRON	1913	88	16	0.30	28	ASPHALT	CLAY	8	1	9	4	2	5	5	4.6	MODERATE
CAST IRON	1935	66	12	0.77	50	ASPHALT	CLAY	8	3	8	2	4	5	5	4.6	MODERATE
CAST IRON/A	1948	53	6	0.74	63	ASPHALT	CLAY	6	5	7	2	6	5	5	4.7	MODERATE
CAST IRON/A	1954	47	6	1.24	69	ASPHALT	CLAY	6	5	7	1	6	5	5	4.5	MODERATE
CAST IRON/A	1952	49	8	0.30	67	ASPHALT	CLAY	6	5	7	4	6	5	5	5.2	MODERATE
CAST IRON	1922	79	6	0.82	37	SEAL	CLAY	8	2	7	2	2	8	5	4.3	MODERATE
CAST IRON/A	1951	50	6	1.66	66	SEAL	CLAY	6	5	7	1	6	8	5	4.6	MODERATE
CAST IRON	1933	68	8	0.94	48	ASPHALT	CLAY	8	3	7	2	4	5	5	4.5	MODERATE
ASBESTOS	1964	37	6	0.30	79	ASPHALT	CLAY	6	7	7	4	6	5	5	5.6	MODERATE
CAST IRON	1940	61	10	0.27	55	ASPHALT	CLAY	8	3	8	4	4	5	5	5.1	MODERATE
ASBESTOS	1959	42	6	0.30	74	ASPHALT	CLAY	6	5	7	4	6	5	5	5.2	MODERATE
CAST IRON	1924	77	12	0.30	39	SEAL	CLAY	8	2	8	4	2	8	5	4.9	MODERATE
CAST IRON	1895	106	6	1.01	10	ASPHALT	CLAY	8	0	7	1	2	5	5	3.5	POOR
CAST IRON	1920	81	10	0.95	35	ASPHALT	CLAY	8	1	8	2	2	5	5	4.1	MODERATE
ASBESTOS	1959	42	12	0.22	74	SEAL	CLAY	6	5	8	4	6	8	5	5.5	MODERATE
DUCTILE IRON	1976	25	6	0.27	91	ASPHALT	CRUSHED STONE	8	8	7	4	8	5	10	7.1	GOOD
CAST IRON	1935	66	6	0.90	50	ASPHALT	CLAY	8	3	7	2	4	5	5	4.5	MODERATE
CAST IRON	1895	106	12	0.21	10	ASPHALT	CLAY	8	0	8	4	2	5	5	4.3	MODERATE
CAST IRON	1937	64	8	0.68	52	ASPHALT	CLAY	8	3	7	2	4	5	5	4.5	MODERATE
DUCTILE IRON	1973	28	6	0.00	88	UNPAVED	CRUSHED STONE	8	8	7	10	8	10	10	8.8	V.GOOD
ASBESTOS	1959	42	10	0.26	74	ASPHALT	CLAY	6	5	8	4	6	5	5	5.3	MODERATE
DUCTILE IRON	1970	31	6	0.19	85	SEAL	CRUSHED STONE	8	7	7	6	8	8	10	7.5	GOOD

Table VI-11 A Sample of Condition Assessment Results for Data-2

INV_ID	LIN_MAT	LIN_NOMIN	LIN_INSTD	AGE	Breakage Rate (Break/Km/Yr)	LIN_AVGCF	Cathd_Prot.	ROAD_TYPE	SOIL_TYPE	PIPE TYPE (AE_{ij})	ROAD (AE_{ij})	SOIL (AE_{ij})	Cathod_Protec_ (AE_{ij})	C-FACTOR (AE_{ij})	BREAK (AE_{ij})	AGE (AE_{ij})	SIZE (AE_{ij})	CONDITION RATING SCORE	LINGUISTIC SCORE
L10074	CI-A	200	1/1/1967	37	1.8	49	No	LOCAL	Silt	6	8	5	6	4	1	7	7	**5.3**	**MODERATE**
L10187	CI-A	300	1/1/1951	53	1.2	63	No	FREEWAY	Silt	6	5	5	6	6	1	5	8	**5.0**	**MODERATE**
L10255	CONC	900	1/1/1922	82	0.0	110	No	FREEWAY	Sand	7	5	10	6	10	10	1	10	**7.0**	**GOOD**
L10259	CONC	600	1/1/1959	45	2.2	110	No	FREEWAY	Silt	7	5	5	6	10	0	5	10	**5.4**	**MODERATE**
L14840	STEEL	600	1/1/1933	71	0.0	50	No	PRIMARY	Clay	10	6	5	6	4	10	2	10	**6.7**	**GOOD**
L10307	CI-A	450	1/1/1967	37	0.0	52	No	SECONDARY	Clay	6	10	5	6	4	10	7	9	**7.1**	**GOOD**
L10343	CI-A	200	1/1/1967	37	0.0	120	No	FREEWAY	Sand	6	5	10	6	10	10	7	7	**7.7**	**GOOD**
L17710	PVC	150	10/6/1972	32	0.0	130	No	SECONDARY	Alluvium	9	10	7	N/A	10	10	7	7	**8.4**	**V.GOOD**
L17711	PVC	100	1/1/1981	23	0.0	130	No	SECONDARY	Alluvium	9	10	7	N/A	10	10	8	5	**8.4**	**V.GOOD**
L10414	CI-A	400	1/1/1968	36	0.4	47	No	SECONDARY	Sand	6	10	10	6	4	4	7	9	**6.9**	**GOOD**
L865	STEEL	600	1/1/1955	49	0.0	87	Yes	FREEWAY	Sand	10	5	10	10	8	10	5	10	**8.6**	**V.GOOD**
L932	DI	600	9/15/1992	12	0.0	120	Yes	PRIMARY	Silt	8	6	5	10	10	10	9	10	**8.5**	**V.GOOD**
L11918	CONC	900	1/1/1963	41	0.0	110	No	ARTERIAL	Silt	7	5	5	6	10	10	5	10	**7.0**	**GOOD**
L13125	STEEL	300	12/1/1993	11	0.0	112	No	FREEWAY	Clay	10	5	5	6	10	10	9	8	**8.2**	**V.GOOD**
L11929	CONC	600	1/1/1960	44	0.0	110	No	ARTERIAL	Silt	7	5	5	6	10	10	5	10	**7.0**	**GOOD**
L11983	CONC	1200	1/1/1958	46	0.0	110	No	ARTERIAL	Clay	7	5	5	6	10	10	5	10	**7.0**	**GOOD**
L12057	CI-A	250	1/1/1988	16	0.0	120	No	PRIMARY	Sand	6	6	10	6	10	10	9	8	**8.3**	**V.GOOD**
L12354	DI	100	1/1/1978	26	4.9	120	No	ARTERIAL	Silt	8	5	5	6	10	0	8	5	**5.7**	**MODERATE**
L12061	CI-A	200	12/28/1988	16	0.0	53	No	LOCAL	Silt	6	8	5	6	4	10	9	7	**7.2**	**GOOD**
L6483	CI	100	1/1/1933	71	0.0	23	No	LOCAL	Alluvium	8	8	7	6	2	10	2	5	**6.1**	**GOOD**
L12094	CI-A	300	1/1/1989	15	0.0	52	No	SECONDARY	Alluvium	6	10	7	6	4	10	9	8	**7.8**	**GOOD**
L12095	CI-A	250	7/27/1989	15	0.0	120	No	SECONDARY	Sand	6	10	10	6	10	10	9	8	**8.5**	**V.GOOD**
L12096	CI-A	200	1/1/1989	15	0.0	50	No	SECONDARY	Silt	6	10	5	6	4	10	9	7	**7.3**	**GOOD**
L17878	PVC	300	8/24/1994	10	0.0	130	No	SECONDARY	Alluvium	9	10	7	N/A	10	10	9	8	**9.0**	**V.GOOD**
L17888	PVC	250	7/3/1995	9	0.0	130	No	LOCAL	Alluvium	9	8	7	N/A	10	10	10	8	**9.1**	**EXCELLENT**
L12109	CI-A	200	1/1/1990	14	0.0	45	No	SECONDARY	Silt	6	10	5	6	4	10	9	7	**7.3**	**GOOD**

VI.4. DETERIORATION CONDITION RATING OF EXISTING WATER MAINS

In this part, the integrated AHP/ANN model is used to develop deterioration curves for different type of pipes. Firstly, the AHP technique is applied to predict the condition assessment values for (Data-2) patterns. Then, these pattern with its' predicted condition values are used to develop a condition rating model using the ANN technique. After validation, arbitrary data are generated with different cases based on different physical, environmental, and operational factors; however, matching the developed ANN model. These data sets are feed into the ANN model in order to get prediction values that can be used to develop prediction curves. The following sections describe these steps.

VI.4.1. Integration of AHP/ANN Models

Neuroshell Predictor Software is used to train and develop the AHP/ANN model. Input and output layer neurons are selected. The number of data points used to train the model is 8093 in which 1500 data points are used in model testing. After training and testing, results show the following;

- Training Network Performance = 0.9895
- Training Average Error = 0.894
- Testing Network Performance = 0.9899
- Testing Average Error = 0.0907

The ANN is recalled for validation purposes. Fourteen percent of the available data set (1500 points) are used for validation of the integrated AHP/ANN model in order to check its capability in predicting condition rating. The AHP/ANN model is validated using equations V-1, 2, 3, and 4 (Chapter V), the results are as follows:

- AIP = 0.0114

- AVP= 0.9886

- Root Mean Square Error (RMS) = 0.00256

- Mean Absolute Error (MAE) = 0.08458

The above results are considered fairly good and acceptable.

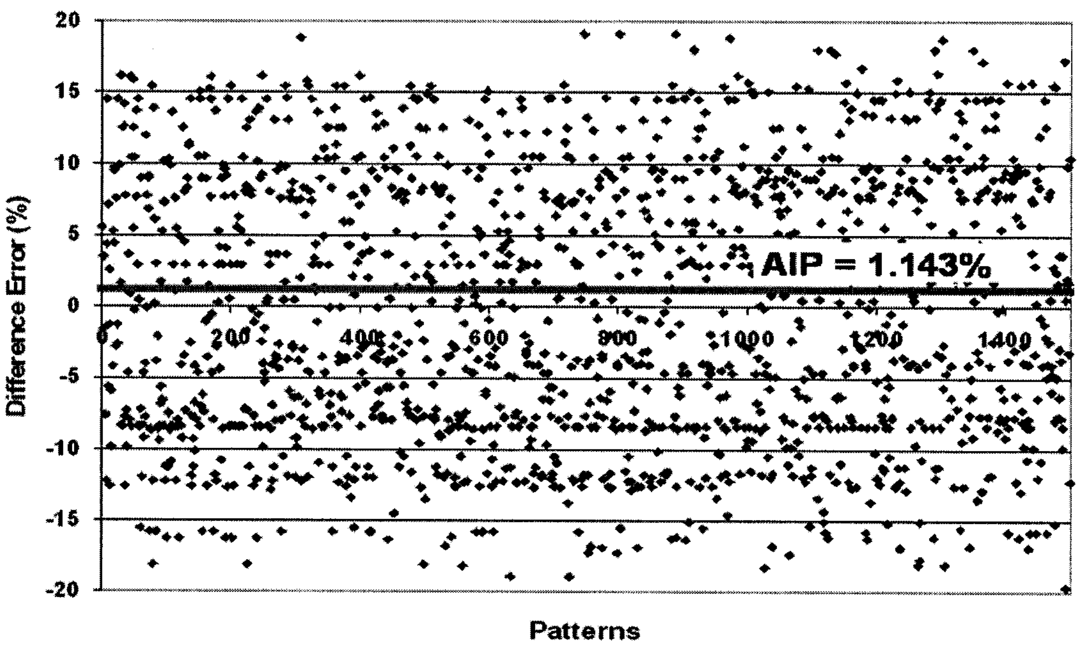

Figure VI-4 Output Difference Error % (Validation Chart-1500 Pattern)

Figure VI-4 shows the output difference error percentage. It shows the scatter plot for the difference pattern points in which the maximum and minimum difference is ranging approximately between $\pm 20\%$ and the (AIP) is 1.143%.

Therefore, the AHP/ANN model is used to predict condition rating based on the different physical (i.e. pipe material, pipe age, pipe diameter), environmental (i.e. soil type, road type), and operational (i.e. breakage rate, C-factor, Cathodic protection) based on their attributes conditions.

VI.4.2. Deterioration Curves

Based on the developed AHP/ANN model, a relation between condition rating (CR) and age is done to predict the (CR) of a water main based on different physical, environmental, and operational factors. Figure VI-5 to Figure VI-8 show a polynomial relation of third degree between the condition assessment and age, as well as Figure E-1 to Figure E-118 in Appendix (E).

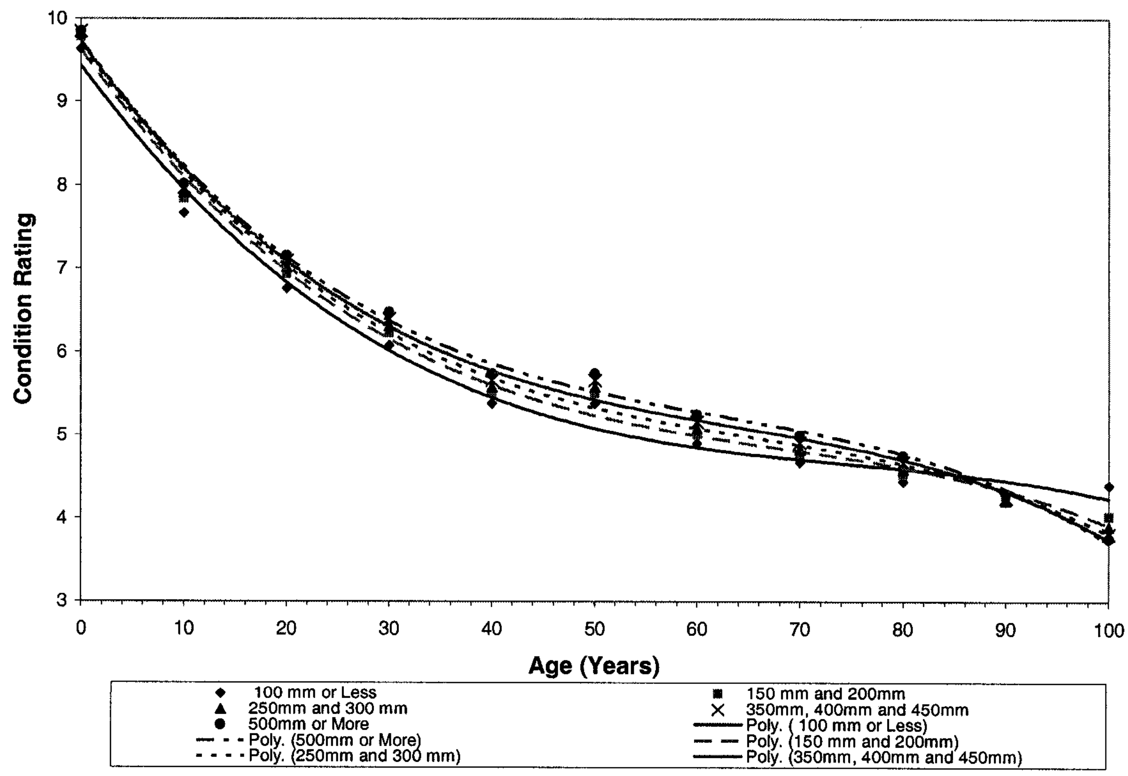

Figure VI-5 Prediction (CR) Curves for Ductile Iron Pipes: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

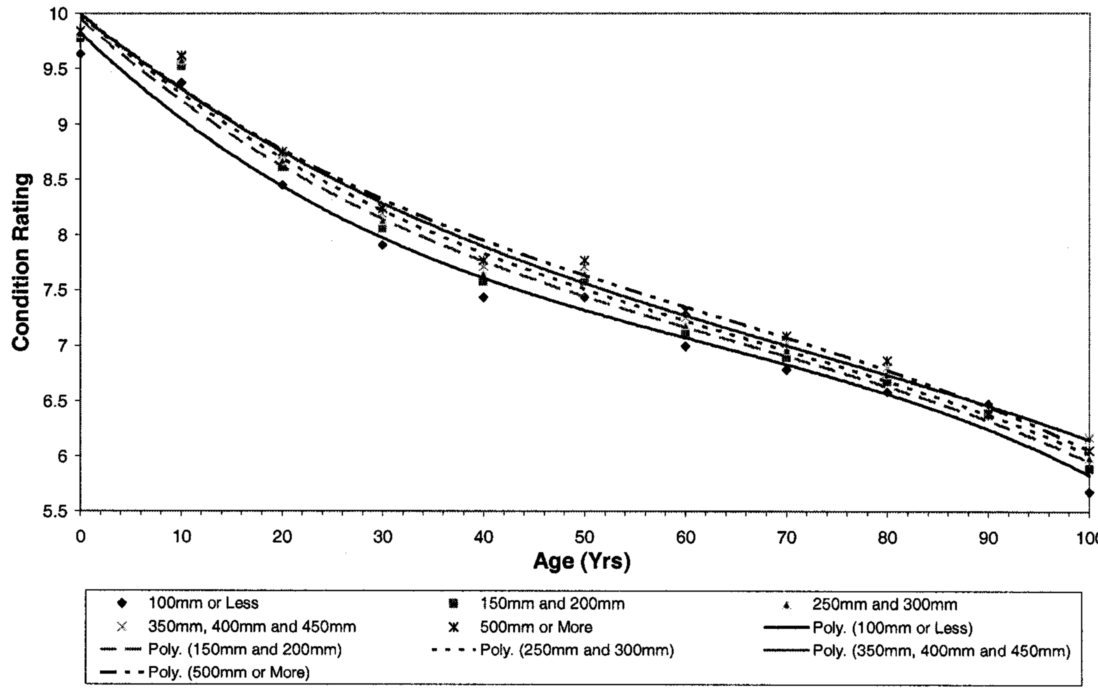

Figure VI-6 Prediction (CR) Curves for Ductile Iron Pipes: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

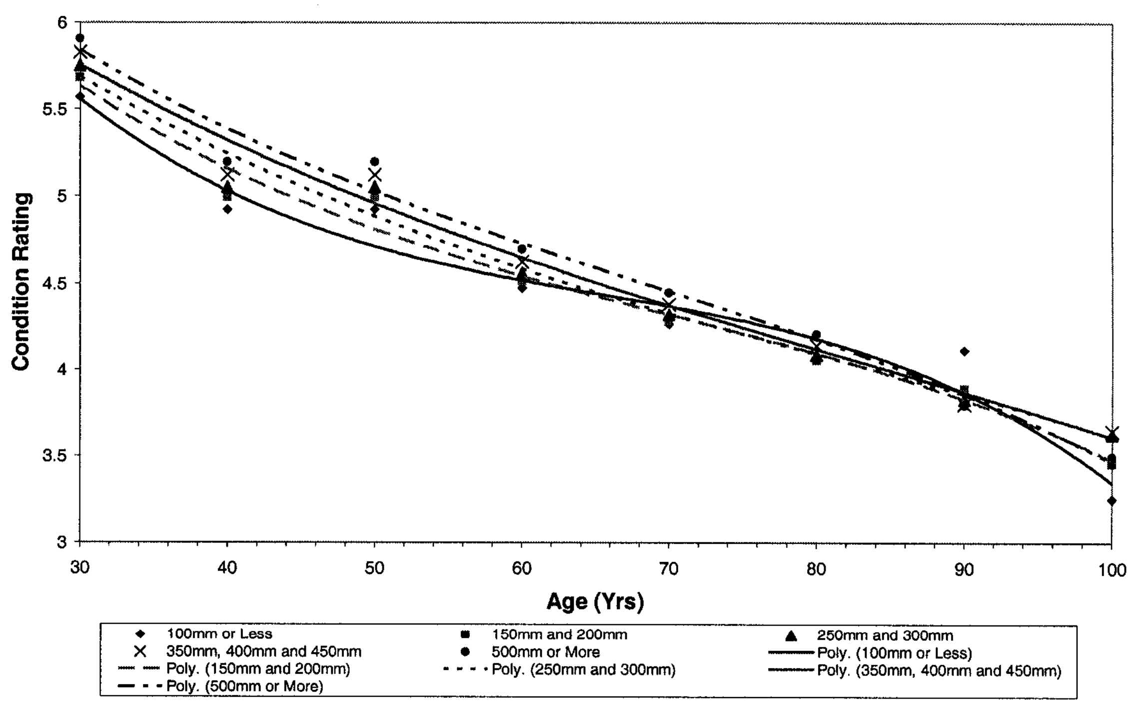

Figure VI-7 Prediction (CA) Curves for Cast Iron Pipes (After WW): C-factor (100) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

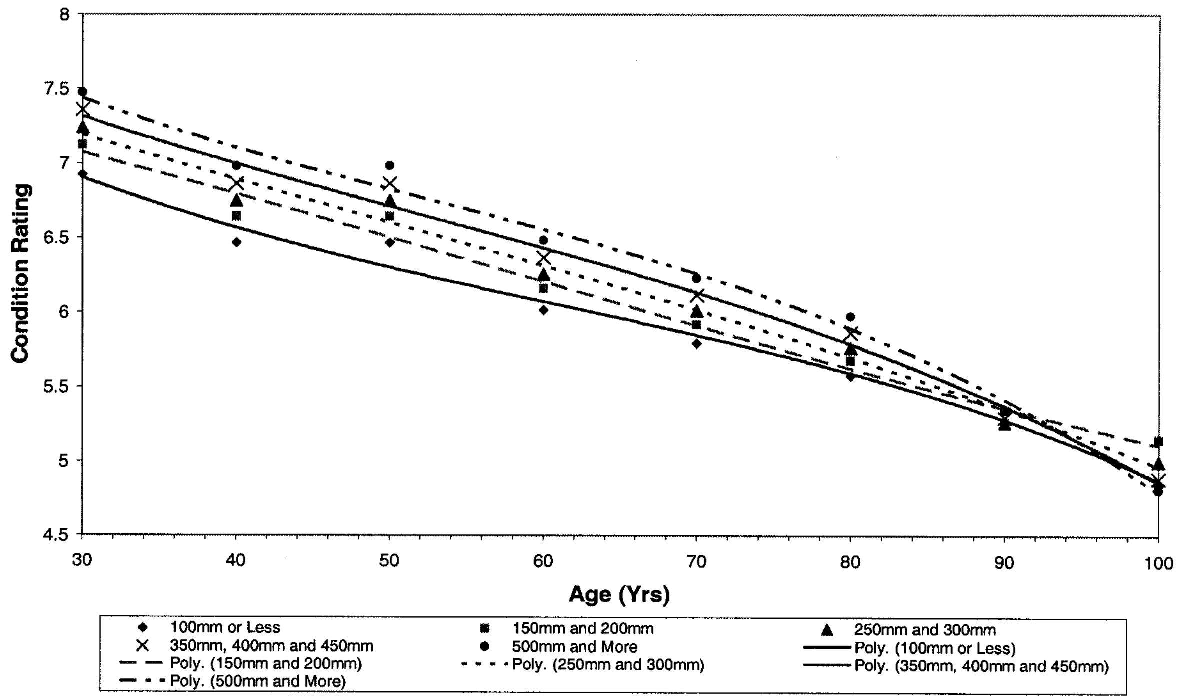

Figure VI-8 Prediction (CR) Curves for Cast Iron Pipes (After WW): C-factor (80) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

It is noticed that all figures show an inverse relation between condition rating and age. For example, Figure VI-5 presents prediction curves for different sizes of ductile iron pipes, with breakage rate of 3, laid in clay soil, C-factor is equal to 120, and has cathodic protection. Based on that figure and under the same condition, if the pipe size and age is known for a specified cast iron water main, municipal engineer can predict its condition rating. So, if it is reported that the age for a ductile iron water main is 80 years, then, the condition rating is 4.5. This means, in reference to Table IV-1, that the cast iron water main is in "Moderate" condition; hence, the municipal engineer has to schedule rehabilitation for such pipe within the next 5- 10 years, and re-assess it in the next 3-5 years.

Based on the developed curves, a relation between condition rating (CR) and Age is done to predict the CR of a water main based on its age. Table VI-12 shows polynomial relations of third degree between the (Age) and (CR) of ductile iron pipes, which represents deterioration curves of Figure VI-5 and VI-6.

X = Age in years

Y= Condition Rating

It is noticed from the results (R^2, adjusted R-squared, standard error, and P-value) that the developed deterioration models are reliable and robust. Therefore, if municipal engineer needs to know the condition rating of ductile iron pipe, under the same conditions of Table VI-12, he/she can select the appropriate deterioration model. For example, if the diameter of ductile iron pipe is 100mm; breakage rate is 3; c-factor is 120; soil is clay; and age is 30 years; then, the condition is "6.05". In reference to Table IV-1, this water main is in "Moderate" condition; hence, the municipal engineer has to schedule rehabilitation for such pipe within the next 5- 10 years, and re-assess it in the next 3-5 years.

The same methodology can be used to develop different prediction curves with their polynomial relations for other types of water mains including concrete, asbestos, welded steel, and P.V.C based on the generated arbitrary data with different conditions.

Table VI-12 Deterioration Models for Ductile Iron Pipes

Case	Pipe Diameter	Breakage Rate (Break/Km/Yr)	C-Factor	Soil Type	MODEL	R Square	Adjusted R Square	Standard Error	P-Value
1	≤ 100mm	3	120	Clay	$Y = -9E\text{-}06X^3 + 0.0021X^2 - 0.1677X + 9.4321$	0.8179	0.7977	0.7484	0.00013
2	150 & 200mm	3	120	Clay	$Y = -1E\text{-}05X^3 + 0.0023X^2 - 0.1737X + 9.6137$	0.8633	0.8481	0.6817	3.5E-05
3	250 & 300mm	3	120	Clay	$Y = -1E\text{-}05X^3 + 0.0023X^2 - 0.1747X + 9.6771$	0.8787	0.8652	0.6506	2.1E-05
4	350, 400, and 450mm	3	120	Clay	$Y = -1E\text{-}05X^3 + 0.0024X^2 - 0.1745X + 9.7163$	0.8908	0.8787	0.6204	1.3E-05
5	≥ 500 mm	3	120	Clay	$Y = -1E\text{-}05X^3 + 0.0024X^2 - 0.1729X + 9.727$	0.9004	0.8893	0.591	8.4E-06
6	≤ 100mm	0.1	100	Sand	$y = -5E\text{-}06X^3 + 0.001X^2 - 0.0876X + 9.8276$	0.946	0.94	0.3011	5.2E-07
7	150 & 200mm	0.1	100	Sand	$Y = -4E\text{-}06X^3 + 0.0008X^2 - 0.0817X + 9.9494$	0.9575	0.9528	0.2719	1.8E-07
8	250 & 300mm	0.1	100	Sand	$Y = -4E\text{-}06X^3 + 0.0008X^2 - 0.0786X + 9.9859$	0.9608	0.9564	0.2609	1.2E-07
9	350, 400, and 450mm	0.1	100	Sand	$Y = -3E\text{-}06X^3 + 0.0007X^2 - 0.0738X + 9.9935$	0.9605	0.9561	0.2574	1.3E-07
10	≥ 500 mm	0.1	100	Sand	$Y = -4E\text{-}06X^3 + 0.0007X^2 - 0.0746X + 9.9982$	0.968	0.9644	0.2331	4.9E-08

DI = Ductile Iron, X= Age, Y= Condition rating, Road Type: Freeway, Cathodic Protection: Yes

VI.5. SUMMARY

Current research designed an AHP condition rating model, which is used as a tool for prioritising and ranking water mains. Eleven sub-factors within three main factors (physical, environmental, and operational) were studied to check their effect on water main conditions. Results show that pipe age has the highest effect on condition assessment (20.95%); then pipe material (17.49%); however, the third factor is the breakage rate (13.13%). On the other hand, the least factor is type of service (2.85%).

Deterioration curves are presented for cast iron and ductile iron pipes. It is developed based on the AHP/ANN model; however, the same frame work can be used to develop prediction curves for other type of pipes. Based on a proposed condition assessment scale, municipal engineer can plan the required rehabilitation actions for water mains. The developed model is relevant to researchers and practitioners (municipal engineers, consultants, and contractors) in order to prioritise pipe inspection and rehabilitation planning for the existing water mains.

CHAPTER VII

WEB-BASED CONDITION RATING MODEL (CR-Predictor)

VII.1. INTRODUCTION

Recent developments in Internet technologies have resulted in improving the quality of life, and developing a wide range of high-speed internet web-based applications. This part presents the process of developing a prototype web-based decision support system for condition rating (CR-Predictor). The system is developed to assist municipal engineers in predicting and ranking the condition rating of existing water mains. The last section of this chapter presents an application example to test the developed system. The application example demonstrates the capabilities of the developed system.

VII.2. CR-Predictor WEB-BASED TOOL FRAMEWORK

The proposed proto-type web-based tool is called Condition Rating Predictor (CR-Predictor). It applies the principles of analytical hierarchy process and/or neural network techniques. The CR-Predictor will assist municipal engineers and experts to predict the condition rating of water mains based on the available historical data at any location.

The CR-Predictor requires information related to priorities and effect values in addition to data related to factors that will be considered in condition rating prediction. The results include condition rating value (0 – 10). The higher value indicates that water main is in "Excellent" condition, and the lower value indicates that water main in "Critical" condition. The flowchart shown in Figure VII-1 summarizes the functioning of the proposed prototype web-based model. It uses the MS Excel to import and export files. However, the inputs for the CR-Predictor vary based on the methodology that will be used for prediction.

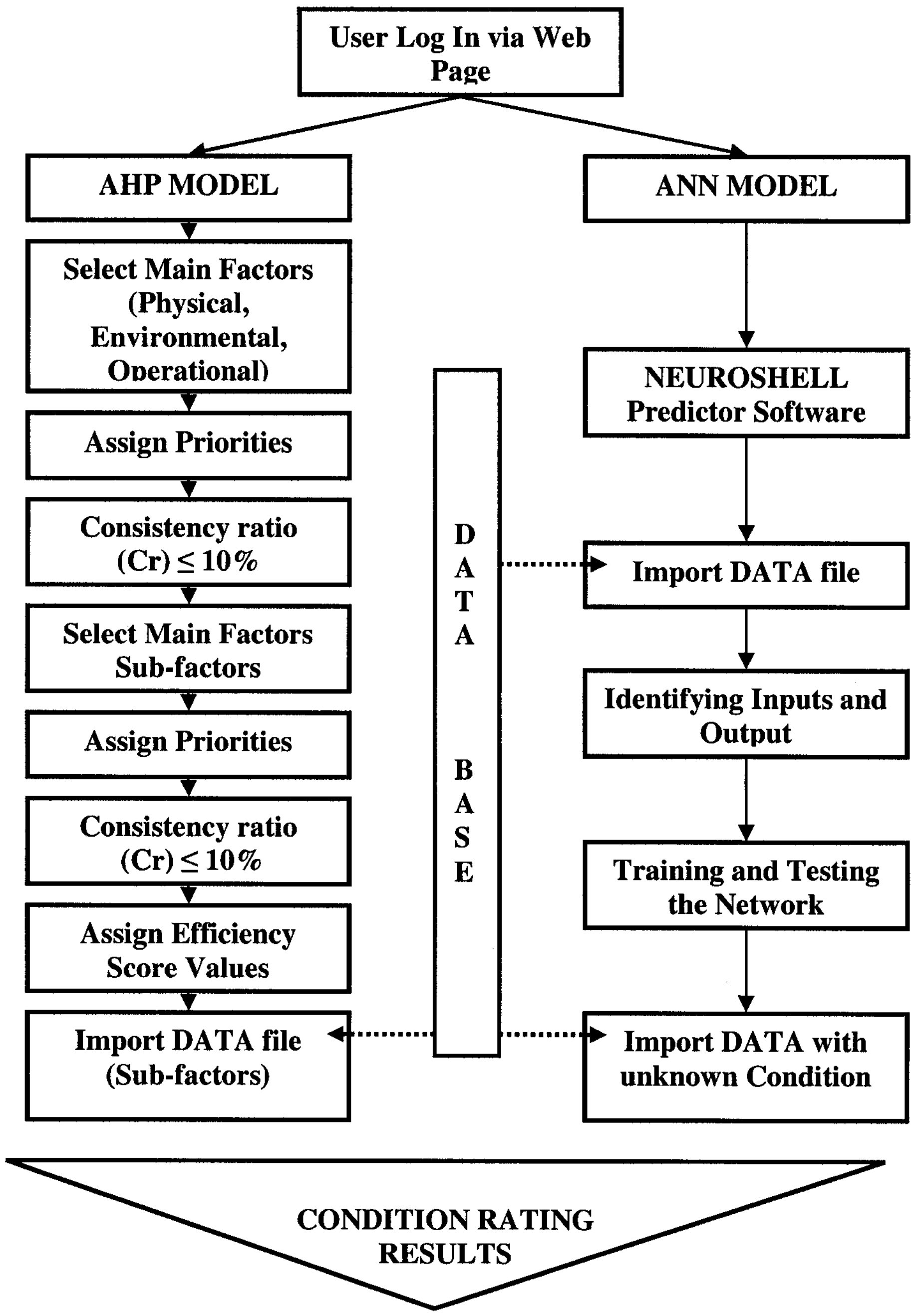

Figure VII-1 Flowchart of the Condition Rating Predictor Web-based System

VII.3. CR-Predictor WEB-BASED SYSTEM

VII.3.1. CR-Predictor Program

The program of CR-Predictor web-based tool is written in ASP (Active Server Page) programming language using th (Visual Studio.Net 2003), environment. The ASP is a web server technology from Microsoft that allows for the creation of dynamic and interactive sessions with the user. It contains HTML and embedded programming code written in VBScript or Jscript. It was introduced with Version 3.0 of Microsoft's Internet Information Server (IIS). When IIS encounters an ASP page requested by the browser, it executes the embedded program. The ASPs are Microsoft's alternative to CGI scripts (Common Gateway Interface) and JavaServer Pages (JSPs), which translates data from a web server and then displays that data on a web page or in an email. This allows HTML pages to interact with other programming applications. The ASP enables the design of a user friendly environment.

The program includes procedure that links executive program, different web-pages, import Excel and decodes data from export Excel files, retrieve data in different tables of the database, perform calculations, and finally generate results.

VII.3.2. CR-Predictor Process

The first page will allow user to register and login as shown in Figure VII-2. The web-page includes a menu bar that enables the user to proceed from one stage to another.

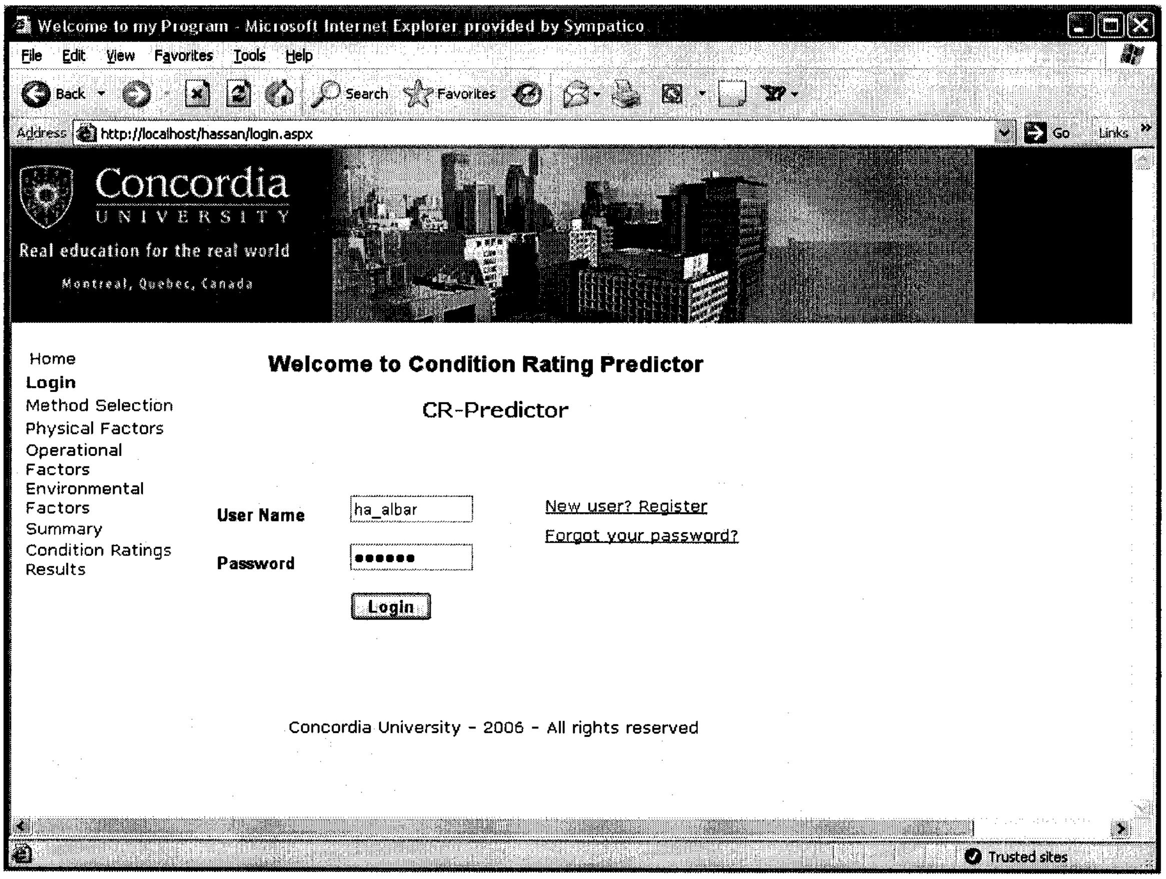

Figure VII-2 Login Schema

After that a web page, shown in Figure VII-3, prompts the user to select the methodology that will be used to predict the condition rating. If the user has historical information concerned the condition rating of the water mains, then ANN approach can be used. On the contrary, if there is no historical information, then user selects AHP approach to predict the condition rating based on his/her own experience. However, integration between the AHP and ANN models can be used to develop AHP/ANN model.

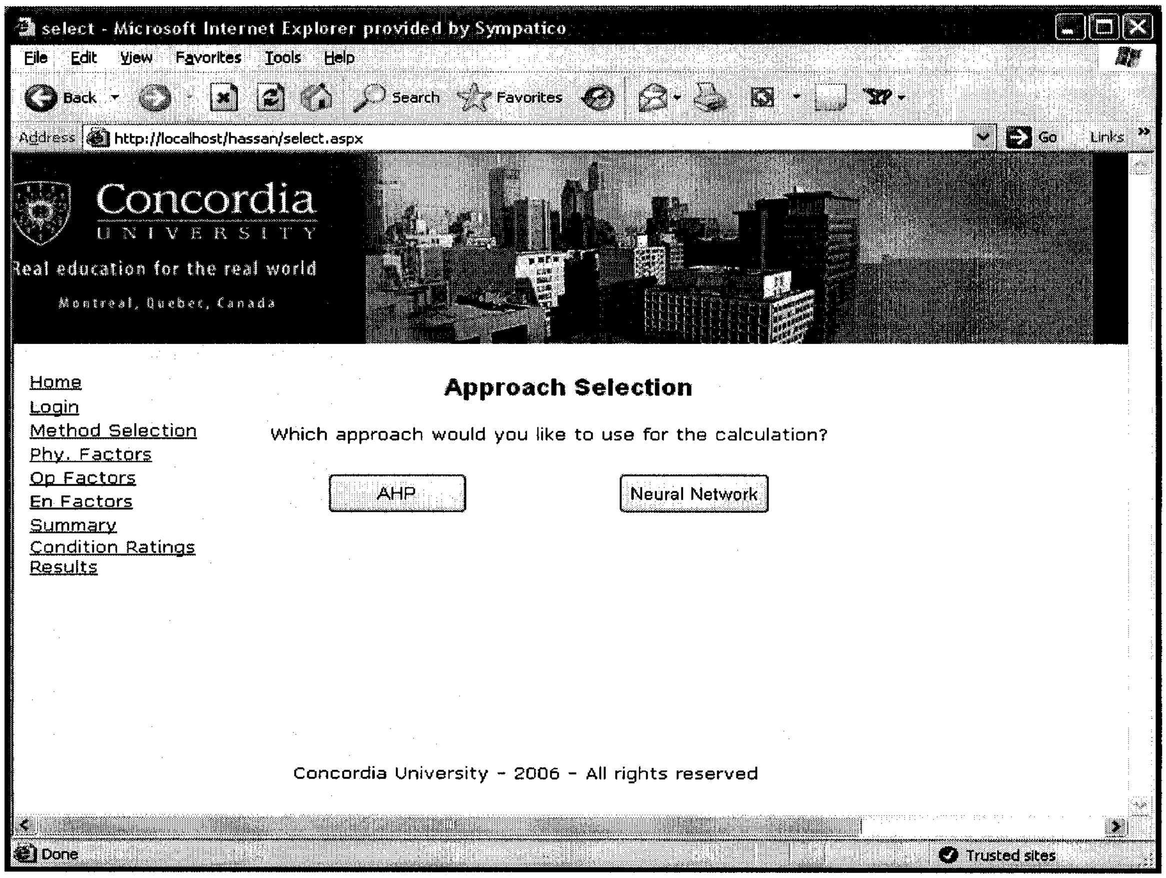

Figure VII-3 Method Selection Schema

VII.3.3. CR-Predictor Calculation Methodology

The calculation in CR-Predictor is performed either by using ANN or AHP technique. Method of calculations and application are presented in detail for both techniques (ANN and AHP) in chapter 5 and chapter 6 respectively.

VII.3.3.1. <u>The AHP Approach</u>

This section presents some of the screens used to enter and display data needed to perform calculations of condition rating using AHP methodology. These screens are also used to view intermediate results of the calculations.

The decision hierarchy of the developed AHP web-page system consists of four levels as shown before in Figure VI-1. The first level represents the condition rating problem. The second level focuses on the main condition rating factors. The third level includes the sub-factors for each category of the main factors. Finally, the fourth level presents the condition rating value ranges from (0-10).

The selection of an appropriate deterioration factors for a certain network depends on different factors that is categorized as physical, environmental, and operational. Each of these factors assists in predicting the condition rating. So, the user has to select firstly the main factors that would be included, and then identify the sub-factors for each category.

The developed condition rating predictor system is designed in a manner to accommodate the user's selection criteria in specifying the sub-factors for comparing the importance of each factor against the other. The prediction is based on a maximum of 27 sub-factors: 9 for physical factors, 9 for environmental factors, and 9 for operational factors. So, the user has the option to select certain sub-factors up to a maximum of 27 sub-factors. The system predicts and ranks the condition rating results based on the user selection criteria and attributes effect values.

When the user selects AHP condition rating approach, the user is directed to general factors web-page, and the system prompts the user to select the main factors that will be included in predicting the condition rating. Then, a pair-wise comparison matrix is performed based on the selected numbers. Then, the user has to fill the relative importance value in the triangle below the diagonal, as shown in Figure VII-4, because the system automatically fills the above triangle by reciprocating the values in the lower triangle. Afterward the user proceeds by pressing calculate button.

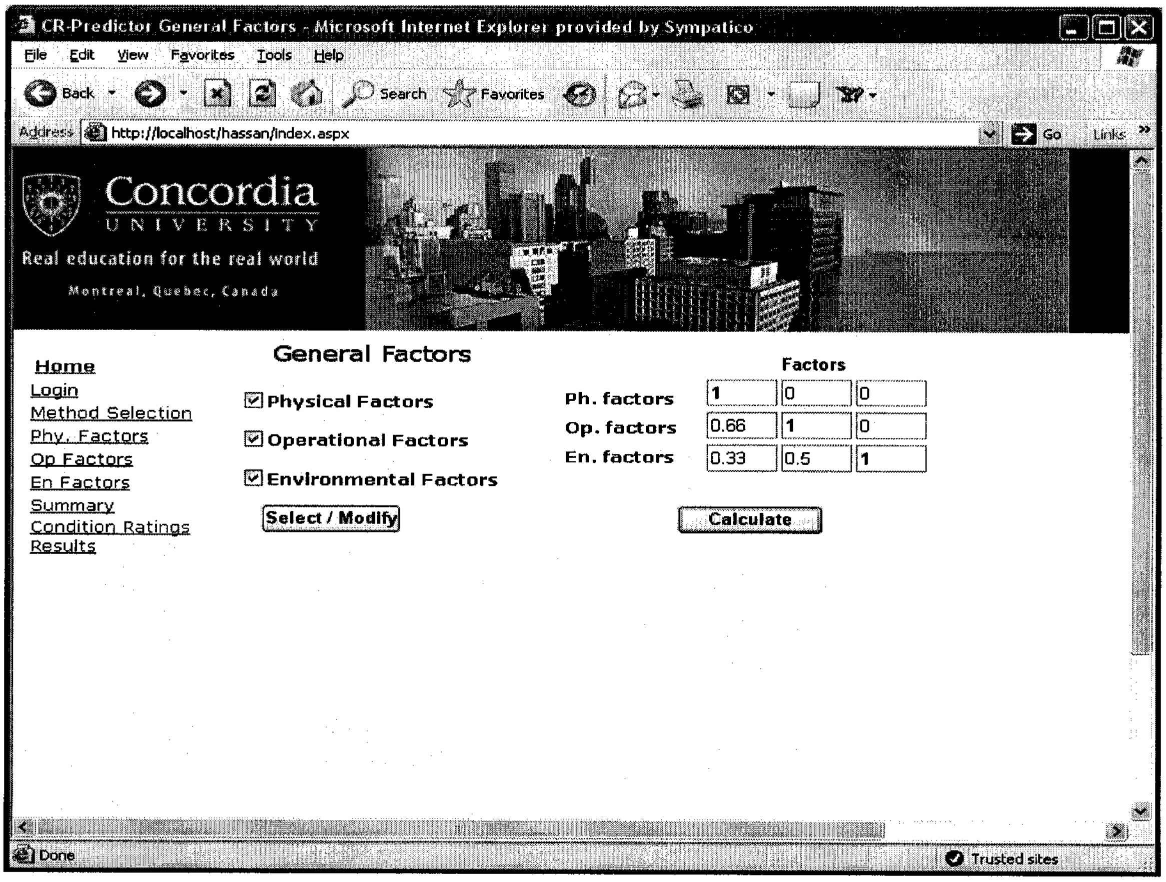

Figure VII-4 General Factors Schema

Summary of results appears as shown in Figure VII-5. The summary includes number of factors considered, priority weights for each selected main factor, consistency index, and consistency ratio. If the consistency ratio is more than 10%, the system prompt the user to modify his/her inputs in the pair-wise comparison matrix. Then, CR-Predictor asked the user to proceed or modify the importance values as requested.

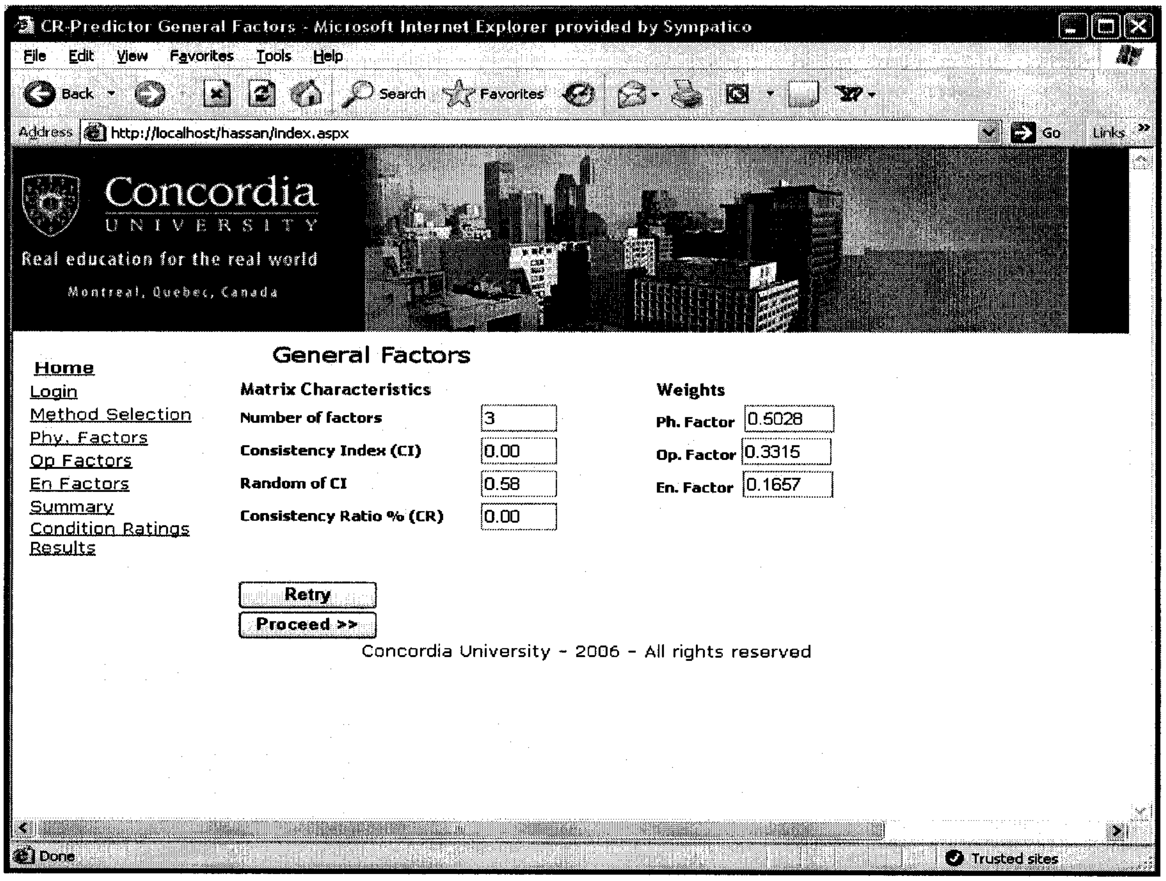

Figure VII-5 General Factors Results Summary Schema

Subsequently, this process is repeated for each main factor selected in general selection step. For example, if the user selects physical factors in the general selection step, the system directs the user to physical factors web-page that lists the physical sub-factors (i.e. pipe material, wall thickness, age, diameter, type of joints, thrust restraint, pipe lining and coating, dissimilar metals, and pipe installation practices). User selects and identifies the sub-factors that would be included in predicting condition rating. Similar to previous step the user gets summary of results as shown in Figure VII-6, before proceeding to other main factor sub-category (environmental or operational) web-page, in addition to the option of generating chart that represent factors weights as shown in Figure VII-7. The user also has the option of modifying both the selection criteria and importance value.

But before proceeding to other sub-factor category, the user has to assign attributes effect value (AE_{ij}) for each selected sub-factor. The assigned (AE_{ij}) value is ranging between "0" for the lowest and 10 for the best, and it is assigned based on municipal engineer experience and the network behaviour. The attributes effect web-page for pipe material and pipe diameter are shown in Figure VII-8 Similarly, this process is repeated if environmental and/or operational are selected.

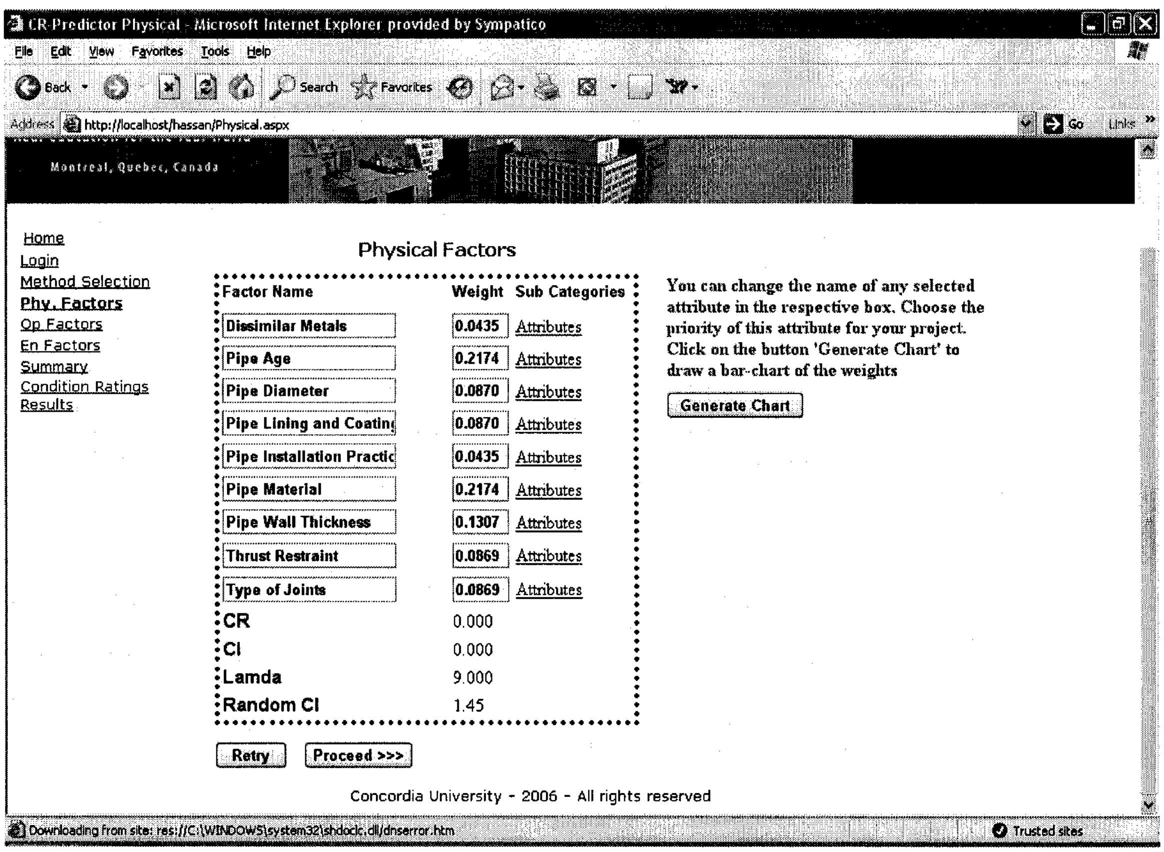

Figure VII-6 Summary of Results for Selected Physical Factors

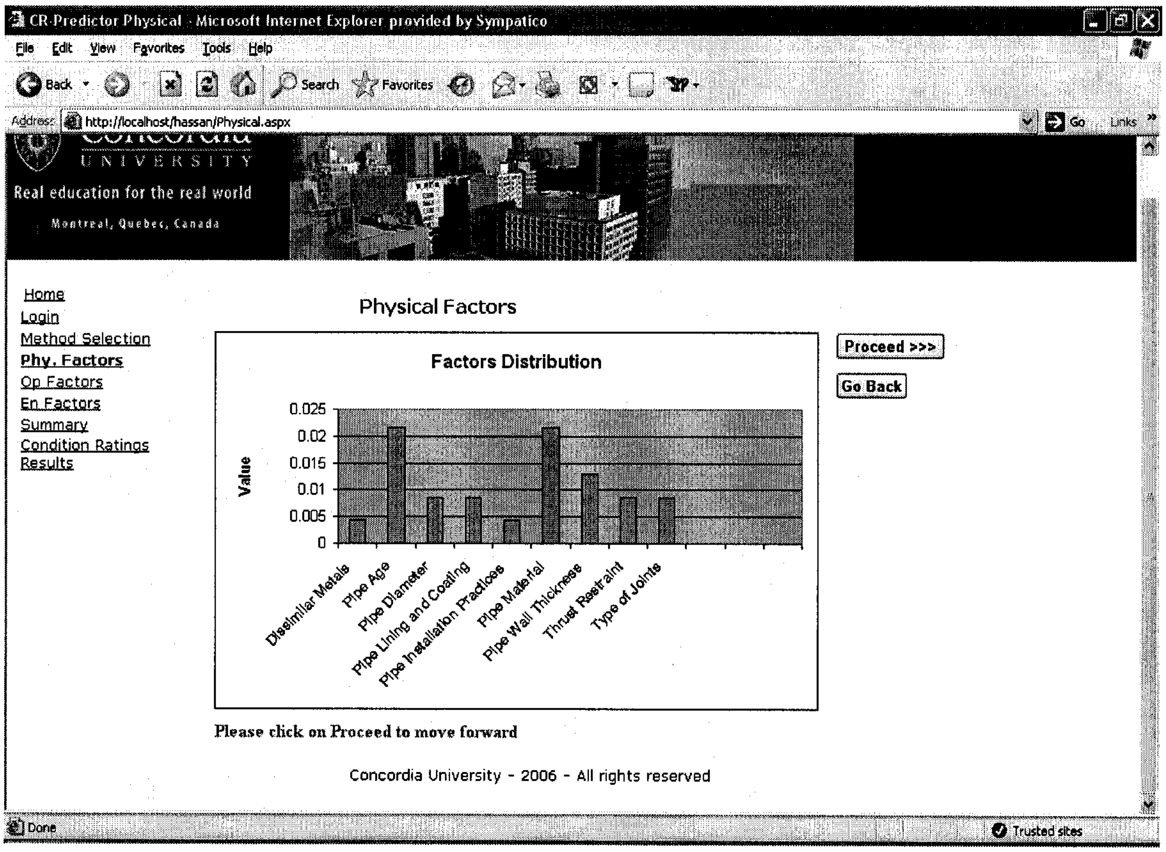

Figure VII-7 Physical Factors Weight Chart

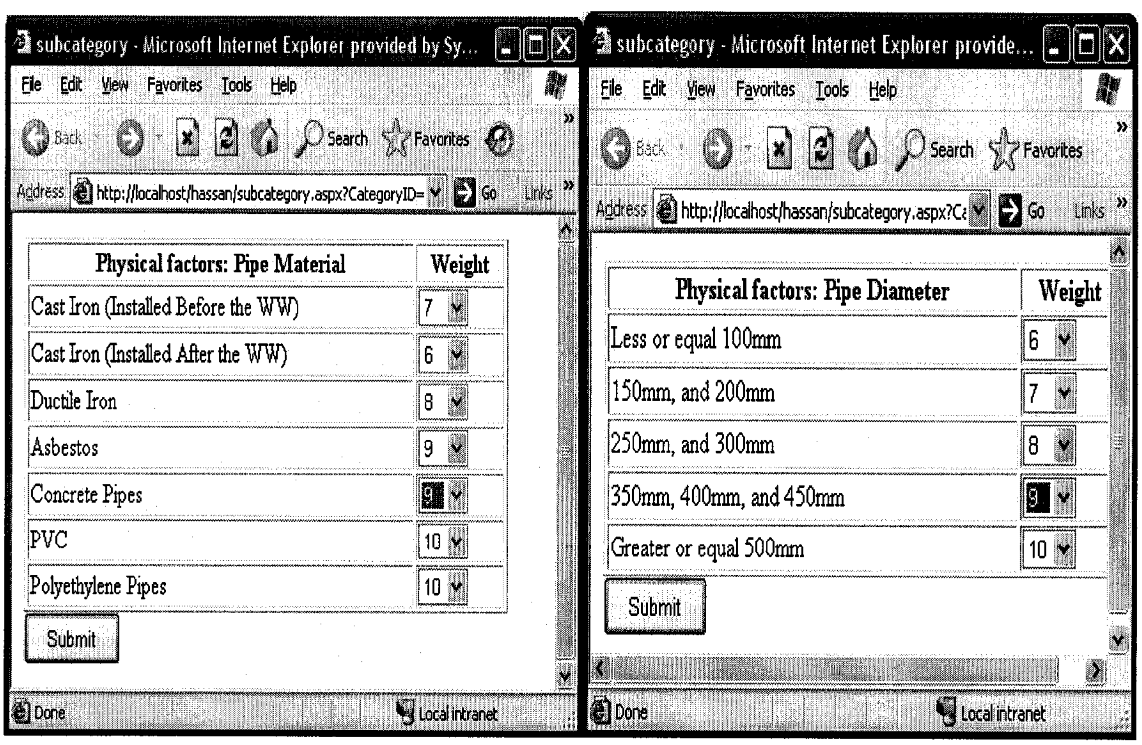

Figure VII-8 Assigning Attributes Effect Values for Pipe Material and Pipe Diameter

Environmental factors include pipe bedding, trench backfilling, soil type, service type, ground water level, frost penetration, pipe location, road type, average daily traffic, disturbances practices, and pipe depth. Operational factors include breakage rate, Hazen-William coefficient, operational pressure, water quality, flow velocity, operation and maintenance practices, cathodic protection, service type, and fire hydrant existence.

After inserting all priority and attributes effect values for all selected sub-factors, the system directs the user to summary results page, shown in Figure VII-9. Then, the system prompts the user to download excel format file to fill data in. After preparing the Excel File, user uploads that file to feed the CR-Predictor with patterns. Finally, the system will do calculations and will prompt the user to get results.

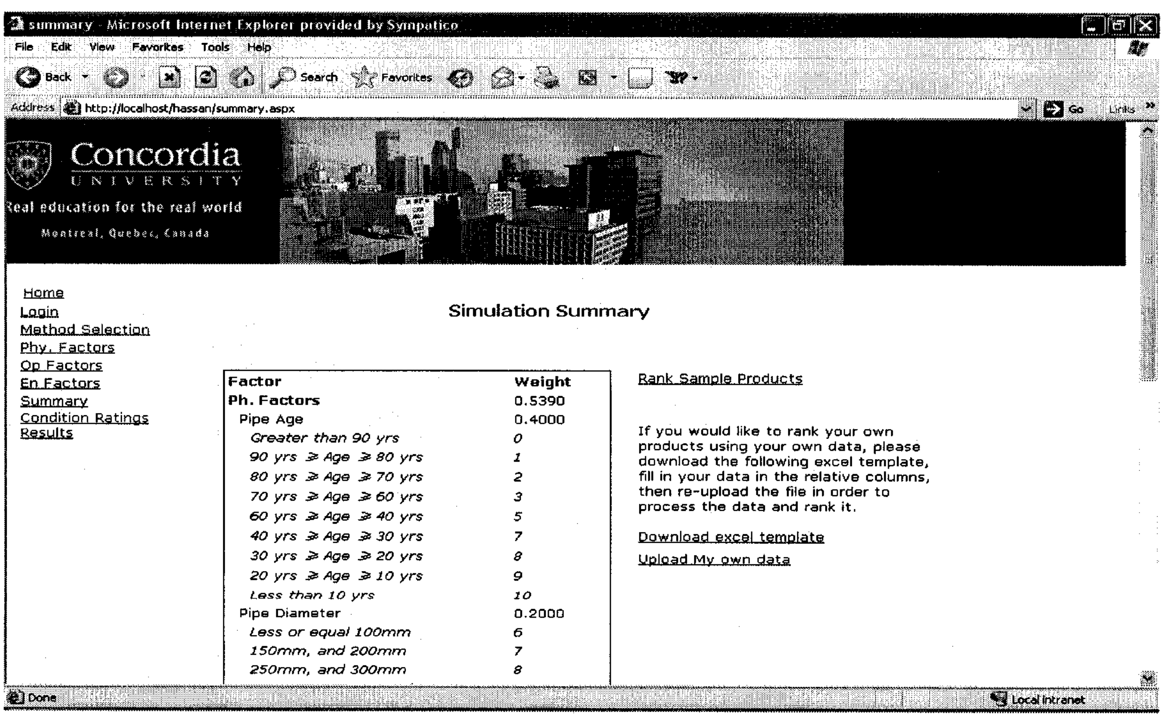

Figure VII-9 Summary Page Schema

VII.3.3.2. <u>The ANN Approach</u>

This section shows some of screens that are used to enter and display data needed to perform calculations of condition rating using the ANN methodology.

CR-Predictor is linked to neural network executive program at the server (Neuroshell Predictor). So, when the user selects to use the ANN approach, he/she is directed to Html page that is linked to the executive program, as shown in Figure VII-10. Afterwards, user follows the instruction used by that program for training and testing (i.e. import historical data file, select input factors and output condition rating values). Then, the ANN model is saved to be used for condition rating prediction, by importing and feeding input patterns into the trained network. The results are displayed on the screen and can be saved as Text file.

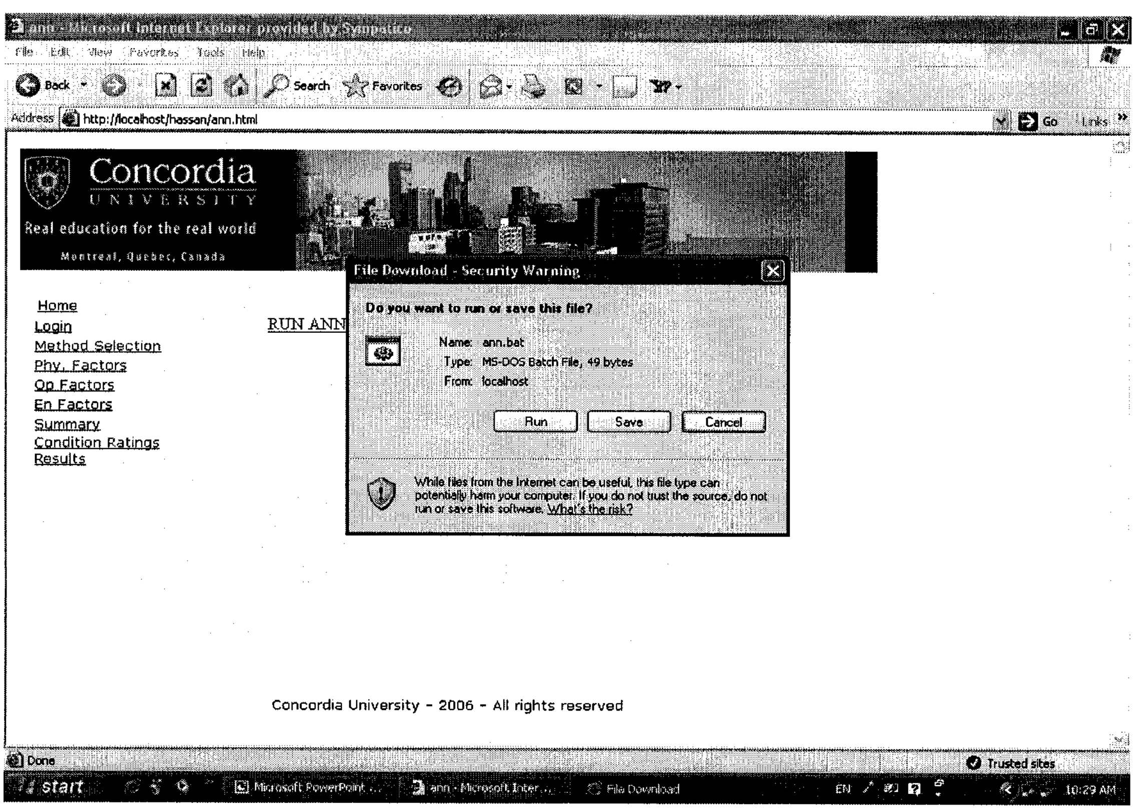

Figure VII-10 ANN Html Schema

VII.4. CR –Predictor RESULTS

The CR-Predictor provides the condition rating results values. The results are displayed in two different forms: (i) on the web-page and (ii) in an Excel file.

The results shown on the web page are displayed and updated along with the advancement of the data entry and selection process. It enables the user to visualize intermediate results of the calculations and appreciates the contribution of different factors on the final results.

The results exported to excel are intended to provide the user with detailed results of the calculations. This practical format is particularly useful for the generation of graphical representations of the results.

VII.5. CR-Predictor APPLICATION

Condition Rating Predictor (CR-Predictor) is used to predict the condition rating values for Data-1 using the ANN methodology and the AHP methodology.

VII.5.1. The ANN Application

The following Figures VII-11 to VII-15 show the window screens retrieved after selecting the ANN methodology.

After selecting the ANN, the user is prompted to run the ANN program, shown in Figure VII-11. Then, the user will be directed to the executive file, which exists at the server, for neural network application.

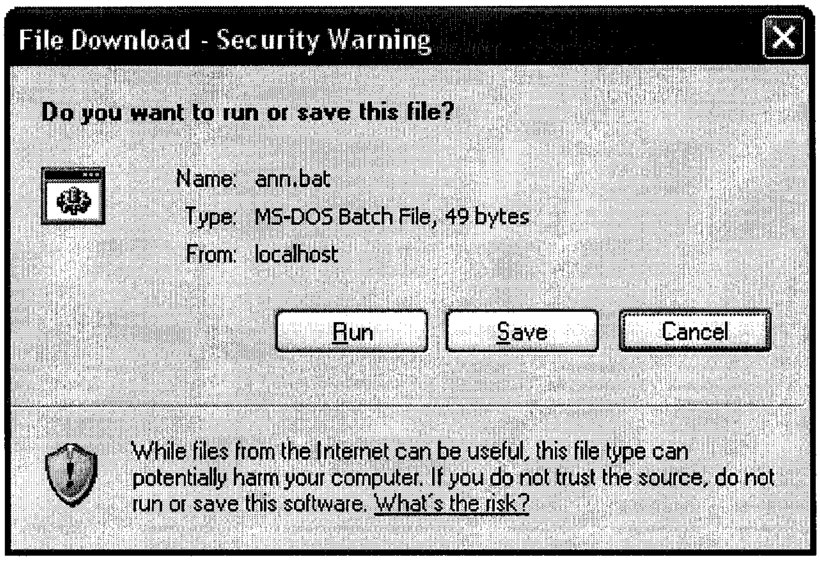

Figure VII-11 Run Schema for ANN Program

First of all, the user has to upload the training file from his/her data base, where the inputs and outputs are known as shown in Figure VII-12.

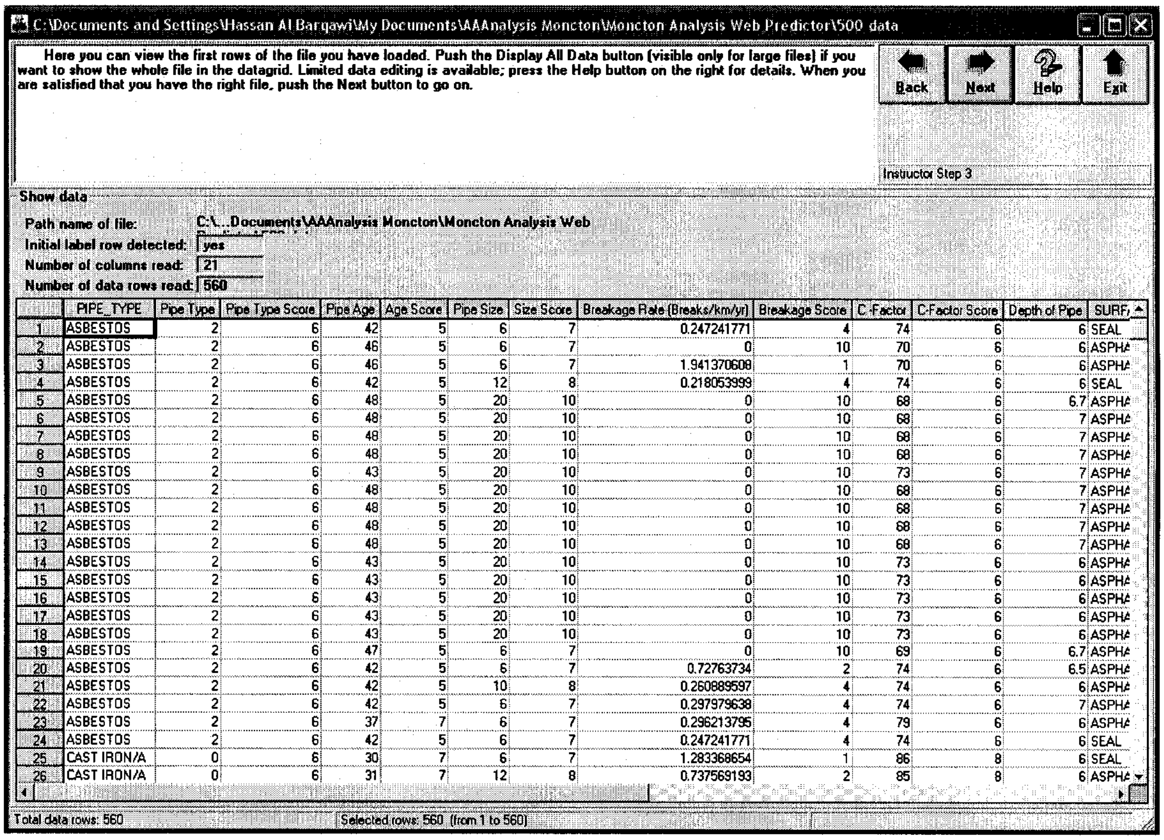

Figure VII-12 ANN Input File Schema

Afterwards, the user has to specify and identify inputs and outputs for training the neural network. Finally, the program executes the training using the back-propagation neural network structure, as shown in Figure VII-13. If the performance of the developed network is satisfactory, user saves the net to use it for future condition assessment predictions. If not, user has to modify his/her selection for the inputs by adding or removing input data for training. And hence, the user has to repeat the modifying process until a satisfactory performance is achieved.

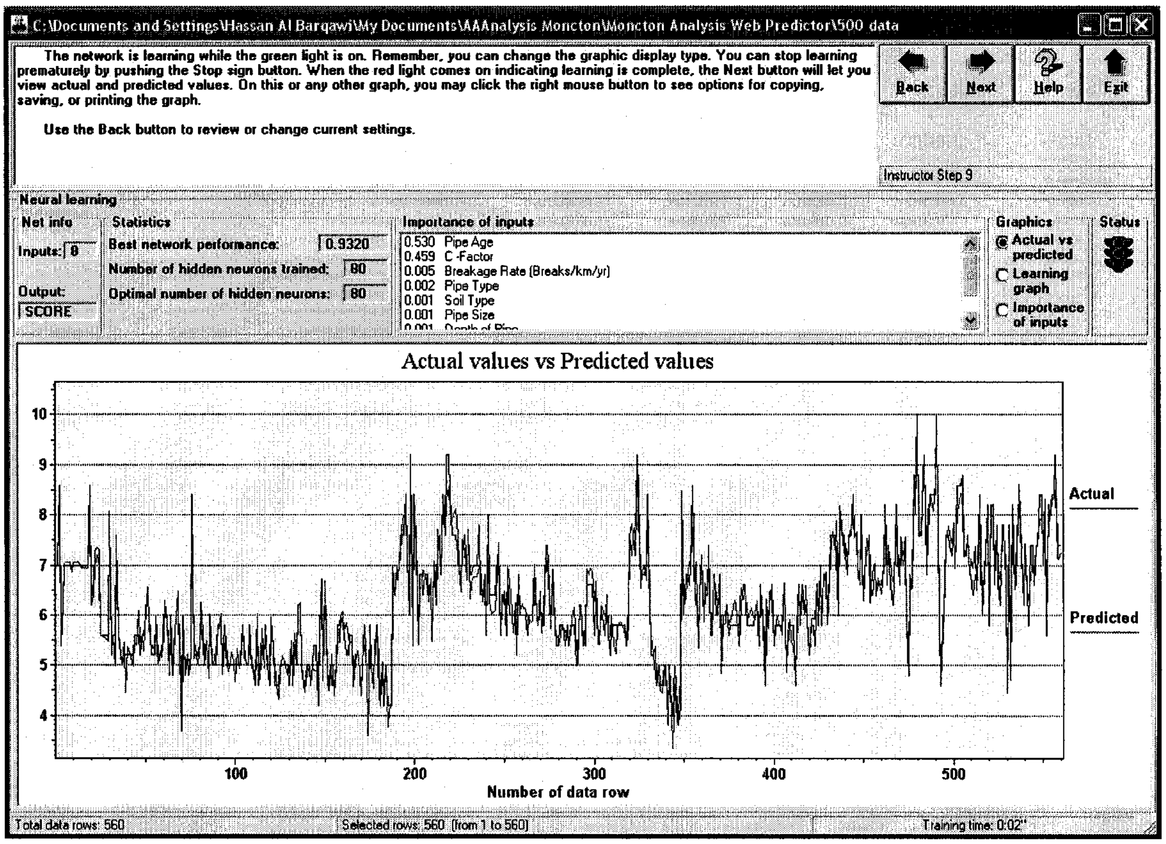

Figure VII-13 ANN Training Results Schema

After getting the satisfactory performance and saving the developed model, user can upload new data file with the same identified inputs and unknown output (condition assessment value) to get prediction results, as shown in Figure VII-14.

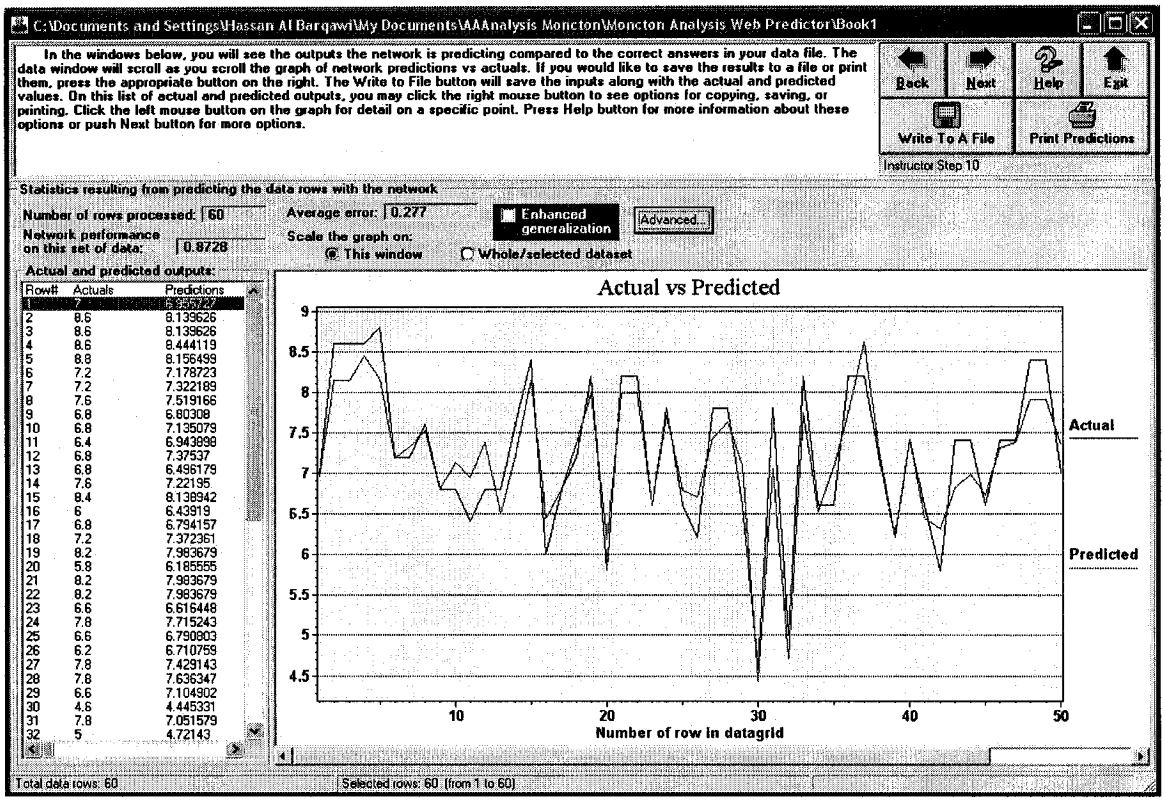

Figure VII-14 Prediction Results Using the ANN

VII.5.2. The AHP Application

The following Figures VII-15 to VII-18 show the window screens retrieved after selecting the AHP methodology. After the user selecting AHP methodology, he/she is directed to general factors web page to select the main factors that will be included in the model, as shown in Figure VII-15. Then, the user assigns the importance value against each selected main factor as shown in Figure VII-16.

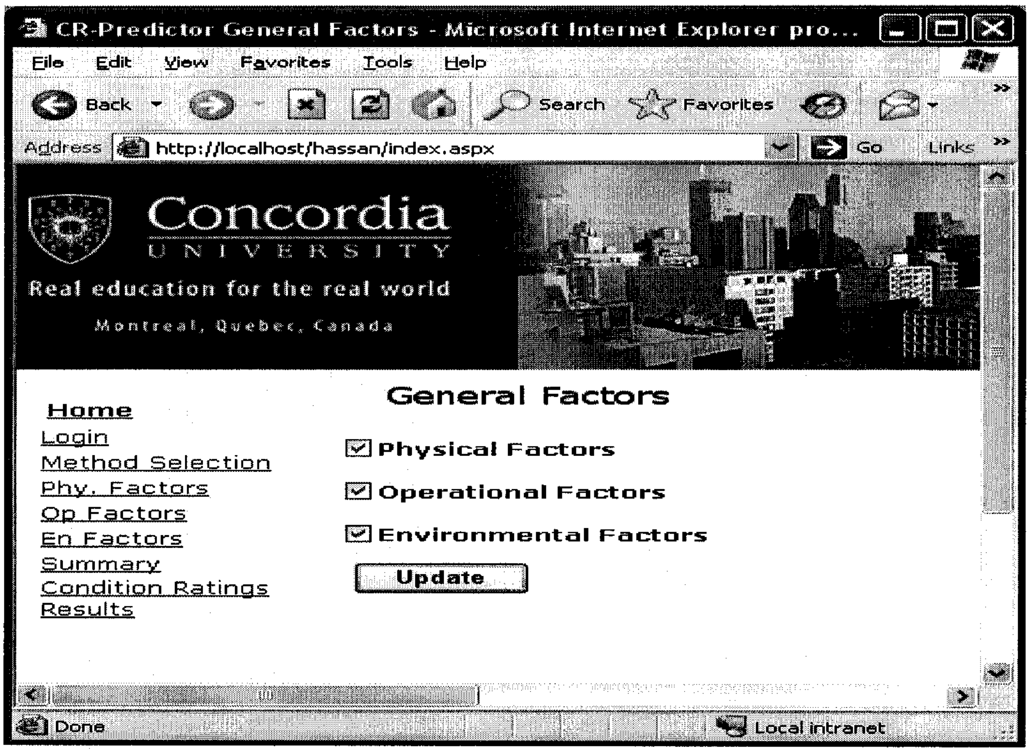

Figure VII-15 Selecting General Factors

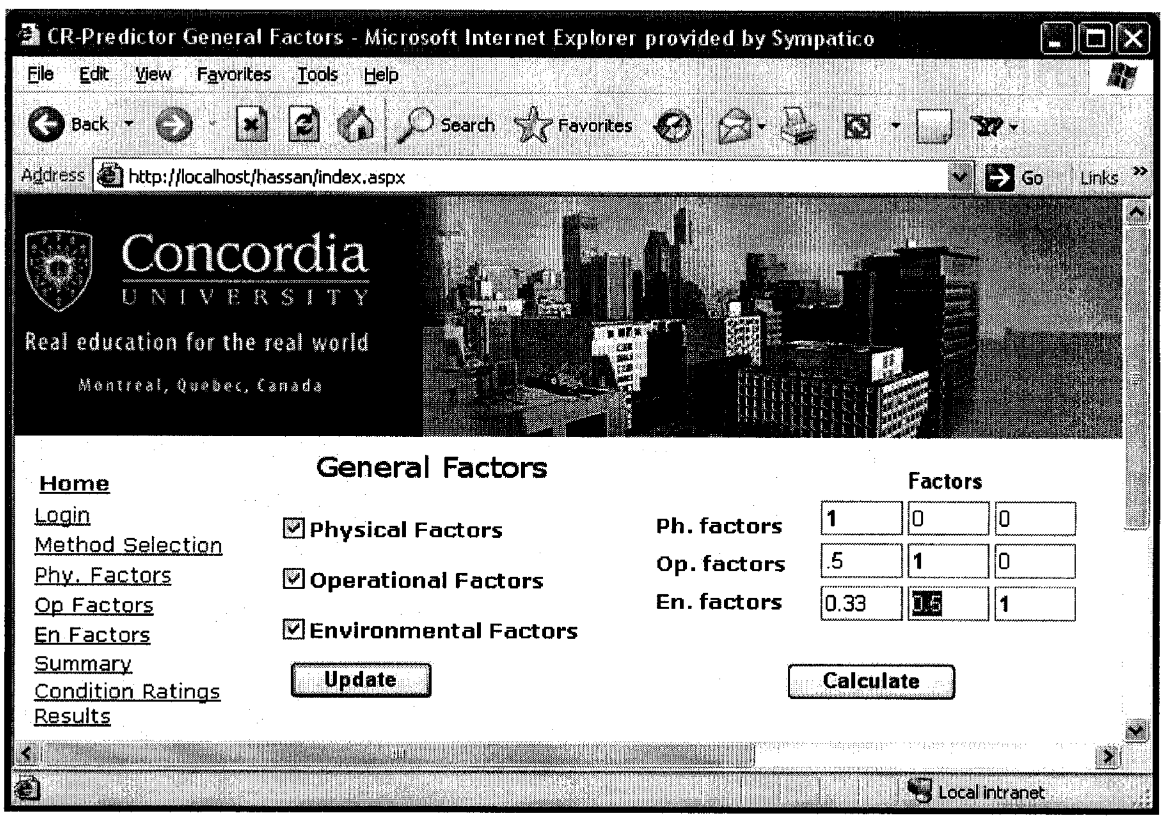

Figure VII-16 User Assign Importance Values

Then, CR-Predictor calculated importance relative weights for the general factors as shown in Figure VII-17. The same methodology is repeated for each selected sub-factors as shown in Appendix (F).

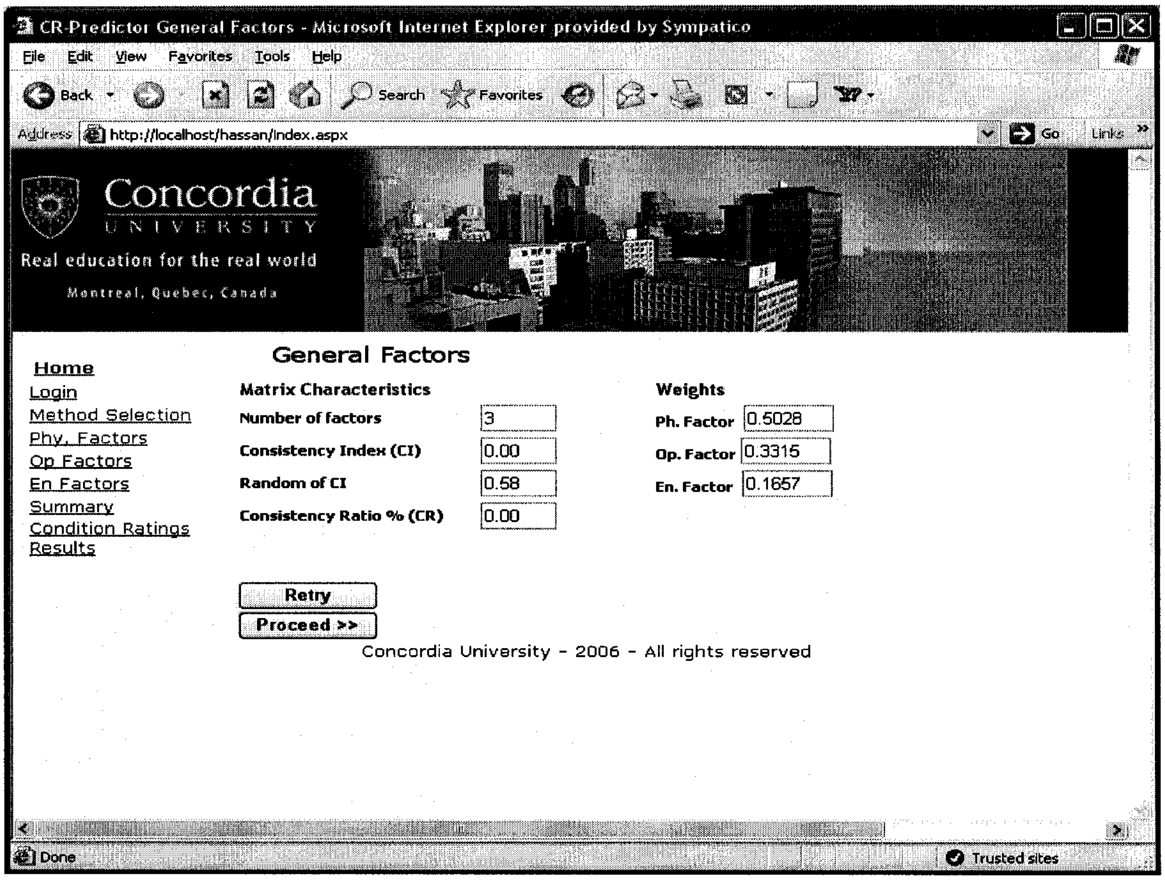

Figure VII-17 General Factors Relative Weights

Finally, CR-Predictor calculates the condition assessment values based on equation (VI-3), as shown in Figure VII-18. Then, the user (i.e. municipal engineer) can prioritise rehabilitation planning based on the condition rating.

Product Name	Material	Age	Diameter	Breaks/km/yr	C-Factor	Cover	Surface Type	Soil Type	Score	Condition
P1	Cast Iron (Installed After the WW)	1961	150	0	76	1.6	Asphalt	Aggressive	6.76	Good
P2	Asbestos	1955	150	0	70	2	Asphalt	Aggressive	6.96	Good
P3	Asbestos	1958	500	0	73	2	Seal	Non-Aggressive	7.91	Good
P4	Asbestos	1958	500	0	73	2	Asphalt	Moderate	7.49	Good
P5	PVC	2000	600	0	120	1.5	Unpaved	Non-Aggressive	9.80	Excellent
P6	Asbestos	1958	500	0	73	2	Asphalt	Aggressive	7.26	Good
P7	Asbestos	1958	500	0	73	2	Asphalt	Aggressive	7.26	Good
P8	Asbestos	1954	150	0	69	2.2	Asphalt	Aggressive	6.91	Good
P9	Asbestos	1953	500	0	68	2.2	Asphalt	Aggressive	7.21	Good
P10	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P11	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P12	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P13	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P14	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P15	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P16	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P17	Asbestos	1958	500	0	73	2.3	Asphalt	Aggressive	7.21	Good
P18	Ductile Iron	1975	600	0.017601493423	90	2	Asphalt	Aggressive	8.03	Very Good
P19	Ductile Iron	1970	150	0.055560593049	85	2	Asphalt	Aggressive	7.23	Good

Figure VII-18 Condition Assessment Score Values

VII.6. SUMMARY

A prototype web-based condition rating system (CR-Predictor) is proposed. It is based on the developed (ANN) model and (AHP) models. Both models could be utilized to predict the condition rating of the water mains. The developed web-based condition rating system in this research can serve as a basis for various further studies. For example, in the case of neural network model, a neural engine could be added to the web-page. This engine will improve the desired friendly-user environment.

CHAPTER VIII

CONCLUSIONS AND RECOMMENDATIONS

VIII.1. CONCLUSIONS

The present research work leads to the development of a numerical and linguistic condition rating scale. The scale is divided into six categories (Excellent, very good, good, moderate, poor, and critical). The characteristics of each category and their associated actions are specified. The proposed scale provides a framework for municipal engineers to plan the required rehabilitation actions of water mains.

Current research work used two different approaches (ANN and AHP) to predict and assess the condition rating of water mains based on identified physical, operational, and environmental factors. The two approaches are employed on the Internet to develop a prototype web-based condition rating tool (CR-Predictor). The first approach uses the ANN technique to develop the proposed model. Average validity percent of this model is 95.74 %, which shows its robustness in predicting water main condition rating for different pipe types. Results show that 71.7% of the outputs are within the 5% difference, 91.7% are within 10% difference, and 100% are within 12.65% difference, which is fairly good and acceptable. Therefore, the proposed ANN model is robust and can be used to predict condition rating of water mains.

It is also concluded that breakage rate has the highest effect on condition rating (30.20%); however, age comes in the second rank (13.60%). Results show an inverse relation between the condition rating (CR) and breakage rate (BR) for most pipe types. A difference between the performance of Cast Iron pipes before and after World War II is noticed.

The second model is developed based on the integration of AHP and ANN approaches to evaluate the sustainability of water mains. The AHP was structured to identify weights of factors that contribute to water main deterioration. Based upon the AHP results, a condition rating model, using ANN, is presented. The integrated model can be used as a tool to prioritize water main rehabilitation projects. Results show that pipe age has the highest effect on condition rating (20.95%); then, pipe material (17.49%); however, the third factor is the breakage rate (13.13%). On the other hand, the least factor is type of service (2.85%). Validation results show the robustness of the developed model (98.86%). Deterioration curves are generated for cast and ductile iron pipes in different conditions. These curves represent a relationship between condition rating and age.

Finally, a prototype web-based condition rating tool (CR-Predictor) is developed based on ANN and AHP approaches. The proposed tool evaluates the condition rating values of water mains based on different physical, environmental, and operational factors that are selected by the user. Results are generated along with their intermediate details in an Excel file or web-browser formats.

The developed models reduce the amount of time and money spent on inspection of existing water mains. They do not completely eliminate subjectivity; however, they are better than the existing prediction methods. The proposed models provide a framework to municipal engineer in order to plan the required rehabilitation actions for existing water mains. They are relevant to researchers and practitioners (municipal engineers, consultants, and contractors).

VIII.2. RESEARCH CONTRIBUTIONS

Current research contributed, to the state of art of water main condition rating for various types of water mains, the following:

- Design a condition rating scale.
- Develop an ANN condition rating model.
- Develop an integrated AHP/ANN condition rating model.
- Build deterioration curves.
- Develop a prototype web-based condition rating tool (CR-Predictor).

VIII.3. MODELS LIMITATIONS

Current research work has introduced two models in addition to the prototype web-based tool (CR-Predictor). They will assist municipal engineers in predicting condition rating of existing water mains. In order to deploy any of the developed models and the CR-Predictor in one municipality, the following should be done:

- There should be a good and reliable database system concerning physical, environmental, and operational factors that would be included the model.

- A random comprehensive condition rating study for the existing water mains should be conducted in order to develop an efficient and reliable condition rating models.
- For the AHP/ANN model, the more experts involved in building the model, the better results they will get.
- For the prototype CR-Predictor, ANN approach, an executive file for neural network should be at the server (i.e. Neuroshell Predictor).

VIII.4. RECOMMENDATIONS & FUTURE WORK

Recommended future work of this research can be described as follows:

- *Current study enhancement areas*:
  - Incorporate more physical, environmental and operational factors to enhance the developed models (i.e. joints type, frost penetration, soil types with more specific characteristics).
  - Enhance the prototype CR-Predictor is required in order to allow the user to modify physical, environmental, and operational factors and to get better analysis and representation for the results (i.e. adding graphical deterioration curves).
  - Integrate the ANN with fuzzy theory (Neuro-fuzzy) to accommodate the inherent imprecision and subjectivity of data.
  - Developing a web-based tool with neural network engine in order to allow for executable file usage of ANN engine.

- *Current study extension areas*:
    - Standardize data acquisition tool for municipalities, which covers more physical, operational, and environmental factors.
    - Integrate non-destructive monitoring and inspection techniques into the developed condition rating models.
    - Incorporate the web-based tool with web-GIS system so that the condition rating of a water main segment can be evaluated separately and automatically.

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APPEDICES

APPEDIX (A)

APPENDIX (A)

A. TYPE OF WATER MAINS PIPES

A.1. Grey Cast Iron Pipes (C.I)

Cast iron pipes have been widely used in water systems and have a long history of satisfactory service. The CI pipes were manufactured from ferrous material in which a major portion contains carbon occurring in the form of flakes spread throughout the metal. Two types of cast iron pipes introduced to the market; the first type is the pit cast iron which was manufactured from the 1880s to the early 1930s by pouring molten cast iron in upright sand moulds placed in a pit. The second type is the spun cast iron which was manufactured in 1920s and 1930s by pouring molten cast iron horizontally in moulds made of sand or metal that spun as the moulds were cooled externally with water. These pipes had better material uniformity than their predecessors with corresponding improvements in material properties (Rajani and Kleiner, 2001). The manufacture of the cast iron pipes was discontinued in the early 1980s.

Cast iron pipes were first employed in North America at the Philadelphia water system in 1800. Currently, more than 14 cities in North America with cast iron water mains still in service after 150 years (Canada Ltd., 2000). In Canada, it is reported in 1993 that approximately 50% of all water distribution pipes were grey cast iron. However, these pipes corrode and deteriorate in aggressive environments, resulting in holes or graphitized areas that weaken the pipe's structural integrity (Rajani et al., 2000).

A.2. Ductile Iron Pipes (D.I)

Ductile iron (DI) pipes were introduced to the market place in 1955. It has been recognized as the industry standard for modern water systems. The DI pipes have proven its strength, durability, and reliability in water systems. They are manufactured from ferrous material in which a major portion contains carbon occurring as free graphite in largely nodular or spheroid form (ANSI/AWWA C110/A21.10); therefore, they are stronger, tougher, and more flexible than cast iron pipes. DI pipe are used in situations where some pipe deflection may occur (i.e. earthquake prone areas) or in soil conditions where settlement of the pipe may occur (Saint-Gobain Inc, 2002; DIPRA, 2001; Canada Ltd., 2000). However, industrial production of ductile iron pipe did not begin until the late 1960s. By 1982 virtually all new iron pipes were ductile iron (Rajani and Kleiner, 2001).

Ductile iron pipes have certain advantages over other pipe materials, (Saint-Gobain Inc, 2002; DIPRA, 2001; Canada Ltd., 2000), such as:

- Low or high pressure applications.
- Corrosion resistant (Internally, coal-tar enamel or cement lining. Externally, external coatings to suit all types of ground conditions and above ground applications).
- High pipe stiffness which minimizes the embedment requirements.
- Full range of diameters and fittings available (DN 80 - DN 1600).
- Variety of jointing systems to suit different ground conditions and pressure ratings.
- Simple and quick to install. Capable of accommodating required pipe work in confined space.

- Hydraulically smooth, because the lining of pipe enhances the ability of the pipe to retain good flow characteristics for many years.
- High beam strength allows pipe to cope with uneven longitudinal loading.
- Resistance to abrasion.

A.3. Welded Steel Pipes (WS)

Welded steel (WS) pipes are used in both water transmission and distribution system mains. They are characterized by their cheap initial construction cost. The WS pipes have certain advantages over other pipe materials, (Ameron Inc, 2002a), such as:

- High strength and high ability to yield or deflect under a load while still resisting the load.
- Capability of bending without breaking and ability to resist shock.
- Easy to handle.
- Different types of joints are available such as bell and spigot joints with O-ring rubber gasket, and lab welded joints.
- Full range of diameters and fittings available up through 144", thickness up to 2", and a standard laying length of 40 feet for operating pressures up to 500 psi.
- WSP pipes have different types of coatings, depending on soil condition such as exterior cement mortar coating, cement mortar coating over coal tar enamel, cement mortar coating over tape wrap, and high density, a dielectric, hot applied extruded polyethylene coating.
- Excellent flow characteristics because of the mortar lining.

A.4. Concrete Cylinder Pipes (CCP)/Pre-stressed Concrete Cylinder Pipes (PCCP)

Concrete and pre-stressed pressure concrete cylinder pipes (CPP/PCCP) are rigid pipes, which are designed to take optimum advantage of the tensile strength and corrosion in concrete. They have been used for over 40 years as water transmission and distribution pipelines. In general, the PCCP has a steel cylinder either outside or embedded in concrete (Ameron Inc., 2002b). The CCP/PCCP pipes have several advantages such as;

- Strong, durable, corrosion resistant, and has a smooth interior which allows high flow velocity with minimal head loss.
- Produced in different diameters (16-144) inch, and in laying lengths of (12-24) ft.
- Installed rapidly and economically by means of self centering steel joints rings sealed with a confined rubber ring. Installation rates of 30-50 pipe sections/day/Installation crew.
- The lined cylinder type is used for pressures up to 250psi, and the embedded cylinder type for pressure upto 350 psi.
- Lower maintenance costs.
- Hydraulic thrust can be resisted by welding the joints ring of the assembled pipe sections for a sufficient distance to develop the required longitudinal restraint.
- Highly resistant to physical damages.
- Relatively inexpensive to build. This makes them attractive when large quantities of water needed to be transferred from the source to the storage system.

A.5. Asbestos Cement Pressure Pipes (AC):

Asbestos cement pipes (AC) are in use since early 1900's. The AC pipes are composed of a mixture of portland cement and asbestos fibers. They are usually unaffected by corrosive soil condition; thus, they have been used in many cases to replace metallic pipes that suffer from excessive corrosion. Similar to cast iron, the AC pipes are no longer being considered as the best alternative. However, the AC pipes have several advantages, (Kalani Inc., 1999), such as:

- Lighter in weight than cast iron and ductile iron pipes.
- Lower cost.
- The design life of AC pipes is 100 yrs.
- Pipe strength increases with age.
- No corrosion.
- Wide range of pipes diameter available (80 – 1000) mm. Standard lengths of AC pipes are 4 m or 5 m.
- Easy to install.
- Different pressure classes are available (i.e. 5,10,15,20 and 25).

A.6. Glass-fiber-Reinforced Plastic (GRP) pipes

Glass-fiber-Reinforced Plastic (GRP) pipes are made of glass reinforcements and thermosetting polyester or Vinyl ester resins. The GRP pipes are used to replace steel and cast iron pipes in water distribution systems, and replace concrete pipes in sewage, drainage and effluent disposal systems (Blaga, 1982). Compared to Ductile Iron, the GRP presents considerable cost savings. It has also certain advantages and features over other types, (Future Ltd., 2004: Johnston Ltd., 2004: Blaga, 1982) such as:

- Cost savings, from the competitively priced unit rates and the cheaper transport-handling costs.
- Short time required for the supply of pipes with the required fittings.
- Easy to handle, pipes and fittings can be unloaded at site without the need for crane, even for large diameter pipes.
- Different types of joints are available such as double bell coupler joint, which used for underground installations, and restrained joints, which used for both aboveground and underground installations.
- Full range of diameters and fittings available range (25 – 4900) mm.
- The number of fittings can be reduced (i.e. one fitting only required for combined angle bends).
- Simple site jointing. Quick and easy to install because of its' lightweight, approximately 1/10th weight of concrete and 1/5th weight of iron pipes.
- Pipes and fittings are available in standard stiffness classes (2500, 5000, and 10000) N/m2.
- Operating pressure classes are available up to 25 bars.
- Excellent flow characteristics, because of the Smooth internal surface which maximizes flow that lead to reduce pumping costs.
- Corrosion resistant, GRP pipes can be used in all natural ground conditions including acidic/alkaline/soils of low resistivity that would require special precautions to install metallic pipes.

- High resistance to abrasion. The internal surface for GRP pipes equal to other plastics and better than cement mortar lining in other pipe materials.

A.7. Polyvinyl Chloride pipes (PVC)/Unplasticised Polyvinyl Chloride Pipes (uPVC)

In the 1930's, Polyvinyl Chloride pipes/Unplasticised Polyvinyl Chloride (PVC/uPVC) pipes were initially developed and used in water distribution system. Plastics are artificial materials based on organic polymers in which a variety of other components are integrated to assist processing and improving the properties of pipes such as fire and weather resistance. The PVC/uPVC pipes have certain advantages over other traditional pipes, (Tyco Inc., 2004; Vinyl Council, 2004; Blaga, 1981), such as:

- Resistance to deterioration and corrosion.
- Easy to handle at site, because (PVC/uPVC) pipes and fittings are lighter in weight comparing to other alternatives, such as concrete and metal pipes.
- High flexibility.
- Strong and durable.
- High chemical resistance
- Excellent flow characteristics with minimal flow loss, because of the smooth bore of (PVC/uPVC) pipe that offers less resistance to flow than other type of pipes.
- Ease of installation, (PVC/uPVC) pipes joined by either Cold Solvent Welding or Rubber Ring Jointing
- Full range of diameters and fittings available range (25- 575) mm.
- (PVC/uPVC) pipes have a pressure class of (100,150 or 200) Psi.
- (PVC/uPVC) pipes have a safety factor of 2:1, compared to the 4:1 safety factor of DI pipes.

A.8. Polyethylene pipes (LD/MD/HD) PE

Polyethylene Pipes (PE) have been used in water distribution system since the 1960's. The PE pipes are used in water distribution system, and also used in house connections to replace galvanized and copper pipes. They are widely used in trenchless pipelines projects which are installed by directional drilling, slip lining and pipe bursting methods. The PE pipes have a high molecular weight and divided into three main categories, according to density:

- *Type I : (0.910 to 0.925) = Low Density (LDPE)*
- *Type II : (0.926 to 0.940) = Medium Density (MDPE)*
- *Type III : (0.941 to 0.965) = High Density(HDPE)*

When the density increases, the stiffness, harness, strength, and heat distortion point increases too. The PE pipes have certain advantages over other traditional pipes (Future Ltd., 2004; Tyco Inc, 2004; Oxford Inc., 2003), such as:

- High resistance to deterioration and corrosion.
- Self-restrained, so no need for thrust blocks.
- Easy to handle at site, because Polyethylene is about one-eighth the density of steel.
- High flexibility and fatigue resistance. It can tolerate severe soil strain and soil movements. Also, it can be bent to a radius 25 times the nominal pipe diameter, which reduce the number of fittings required to change direction.
- The "allowable water leakage" is zero, which is differing than typical leakage rates of 10 to 20% for (PVC) and Ductile Iron.
- Strong and durable.
- High chemical resistance

- Excellent flow characteristics with minimal flow loss, because of the smooth bore of PE pipe and no tuberculation over time.
- PE pipes are joined by Butt fusion, Electro fusion or Compression fitting. The weld joint is as strong as the original pipe or stronger.
- The design life for PE is (50 – 100) Years.
- Full range of diameters and fittings available range (13 – 1575) mm. PE pipes are produced in straight lengths up to 50 ft long and coiled in diameters up through 6”, and over 1000ft length.
- Operating pressure classes are available up to 20 bars and the maximum design temperature is 70° C and the minimum is -20° C.

APPEDIX (B)

APPENDIX (B)

B. TECHNIQUES USED TO ASSES CONDITION OF OTHER INFRASTRUCTURE FACILITIES

B.1. Methods Used Commercially for the Condition Assessment of Buried Storm and Wastewater Sewer Pipes

This section presents an overview of current methods used to assess sewer pipelines, including internal and external inspection technologies.

B.1.1. Smoke Testing

Smoke testing technique began to be used in the early of 1960s. It is considered to be an effective method of inspecting sewer systems, for its economic and time saving. Simply, the system that needs to be inspected is isolated (i.e. sand bags, stoppers or rubber flanges), in order to confine the smoke. After that, a non-toxic smoke liquid or bomb is placed, in the isolated section in a manhole, along with blower equipment as shown in Figure B-1.

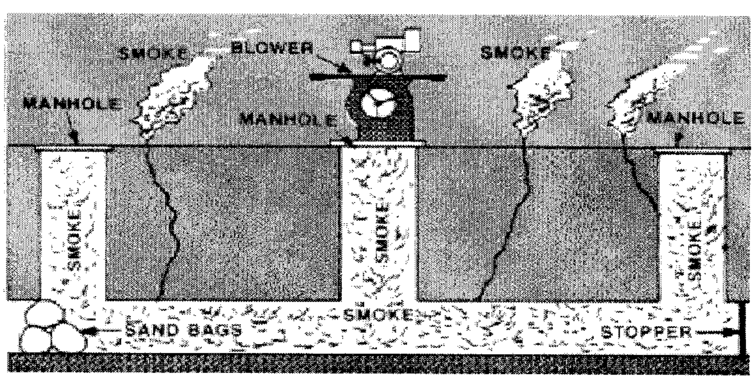

Figure B-1 A Typical Smoke Testing Operation (Adapted from Alloche et al.,2002)

Then, the blower is operated to push smoke through the system. When the smoke appeared filtering out of the pipe, cracks or legal and illegal sanitary connections can be located (Allouche et al., 2002). Also, smoke testing technique is used to verify the location of buried manholes or diversion points in the system (Ratliff, 2003). However, smoke testing technique can not detect and locate small leaks (Tafuri et al., 2002)

B.1.2. Dye Testing

Dye testing technique is used to detect and verify the illegal flow of effluent from factories through the sewer system, or if wastewater is overflowing or leaking into a creek or river. Also, it can be used to locate unrecorded connections of storm water drains through the sewer system. In brief, one operator applies a non-toxic powder or tablets dye into drains and mixes with fluid carried by the pipe, resulting in a clear visible color that can be obviously seen. Another operator maintains watching the inspecting manholes downstream locations. (Allouche et al., 2002; Ratliff, 2003). However, dye testing technique can not detect and locate small leaks (Tafuri et al., 2002).

B.1.3 Visual Inspection

This technique considered as the most elementary inspection method. It depends mainly on men entry, involving the physical inspection of the pipe's interior by a trained technician (Allouche et al., 2002) However, physical inspection by workers is becoming less popular because of high expenses associated with labor costs and safety considerations to personnel and surrounding structures. Moreover, the pipe's interior inspection is limited by the size of the inspected pipe. (Allouche et al., 2002; Tafuri et al., 2002).

B.1.4. Closed Circuit Television (CCTV)

CCTV considered being the most common technique used for the inspection of sewer system (Makar, 1999; Allouche et al., 2002). It is the most common technique used of inspection for small to medium diameter pipes (Ratliff, 2003). In this technique a CCTV mobile camera surrounded with small and high intensity lights is attached to a mobile robot placed into pipeline, and connected to a monitor that allows the operator monitoring and recording location and observation of deficiencies in pipes as shown in Figure B-2. Images can be stored on videotape or in CD-ROM format, so the Engineering staff can be able to review or copy images at any time (Allouche et al., 2002). Video storage improvements have been done to CCTV units such as storage on compact disk (CD) or digital video disc (DVD) that doesn't lose quality over time, use, or copying (Ratliff, 2003).

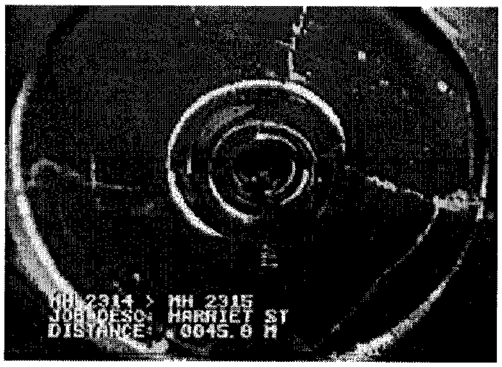

Figure B-2 CCTV Scan of a Pipe Section (Adapted from Alloche et al.,2002)

CCTV inspection technique provides visual information about the condition of the interior surface of the inspected pipe, but it is difficult to detect minor defects as they can be obstructed by tuberculation or mud (Allouche et al., 2002). The success or failure of results in this technique is subjected mainly on the operator's level of inspection knowledge and experience (Allouche et al., 2002; Tafuri et al., 2002).

B.1.5. Zoom Camera Technology

In this technique truck-mounted camera equipment with long-range zoom lens and powerful halogen spotlights are used in conducting visual inspections of manholes and sewers. By using a monitor located in the truck, the resolute image is displayed and recorded for review and analysis to evaluate manholes and sewer condition as shown in Figure B-3. In comparison with conventional CCTV, Zoom camera technique is more economic and time saving since it doesn't require any cleaning of the pipes and manhole entries (Allouche et al, 2002; InfraMetrix, 2003).

Zoom camera technique is commonly used in performing an initial inspection, by collecting data that determines which sections of pipe need to be inspected using a more adequate technique. However, this technique is limited by the depth of penetration of spotlights. For example, if the pipe is smaller than 250mm diameter, the typical operating range for zoom cameras within the pipe is 25m. But if the pipe diameter is larger, the operating range can reach up to 50m (Allouche et al, 2002).

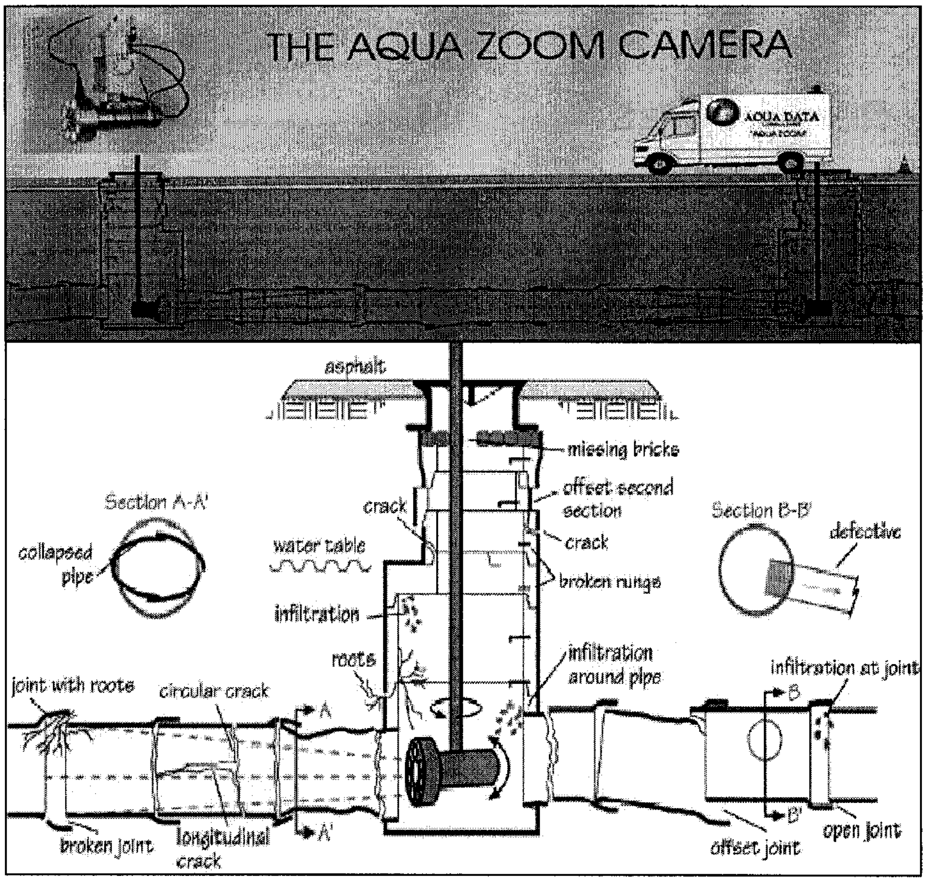

Figure B-3 Zoom Camera approach (Adapted from InfraMetrix, 2003)

B.1.6. Sewer Scanners and Evaluation Technology (SSET)

In January 2001, Sewer Scanners and Evaluation Technology (SSET) system was introduced for the first time in commercial market (Chae et al., 2003). It has been developed to overcome some of the limitations of the conventional CCTV technique. SSET uses a combination of scanner and gyroscope systems that provide the ability of recording 360 degree high resolution digital uniform scanned 2D images, as shown in Figure B-4. It also measures horizontal and vertical deflection and actual pipe interior diameter through the use of the gyroscope system.

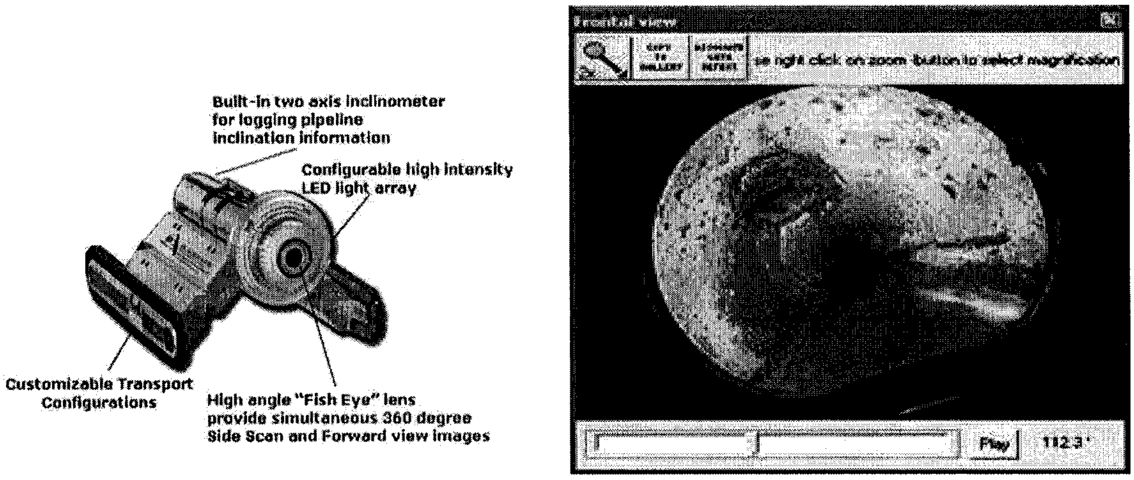

Figure B-4 SSET Survey Machine and Some Typical Output (Hydromax, 2004)

The collected data allows the engineer, not the camera operator, to monitor and view the total surface of the inspected pipe vertically and horizontally, and evaluate all the defects (Allouche et al.; 2002; Ratliff, 2003).

Because data captured by SSET is in digital form, it is readily amenable to computer assisted and/or automated analyses. Digital images can be compressed and stored on CDs or DVDs. SSET generate the defect list tables automatically either sorted by the distance or by the defect type (Chae et al, 2003).

B.1.7. Ground Penetrating Radar (GPR)

The main use of GPR is to detect and identify the location and depth of buried pipes. Also it is used to identify voids location that exists in the soil surrounding the pipe. In this technique the GPR emits pulses of radio waves into the ground and measures the strength and delay time of the reflection and refraction waves by subsurface layers or buried objects. Generally, GPR can detect utility lines at a depth equal to 8-12 times their diameter. However, the depth of penetration can reach up to 100 meter depending on type of soil, as shown in Figure B-5, diameter of pipe, composition and properties of the flow materials, and the radio frequency emitted by the transmitter.

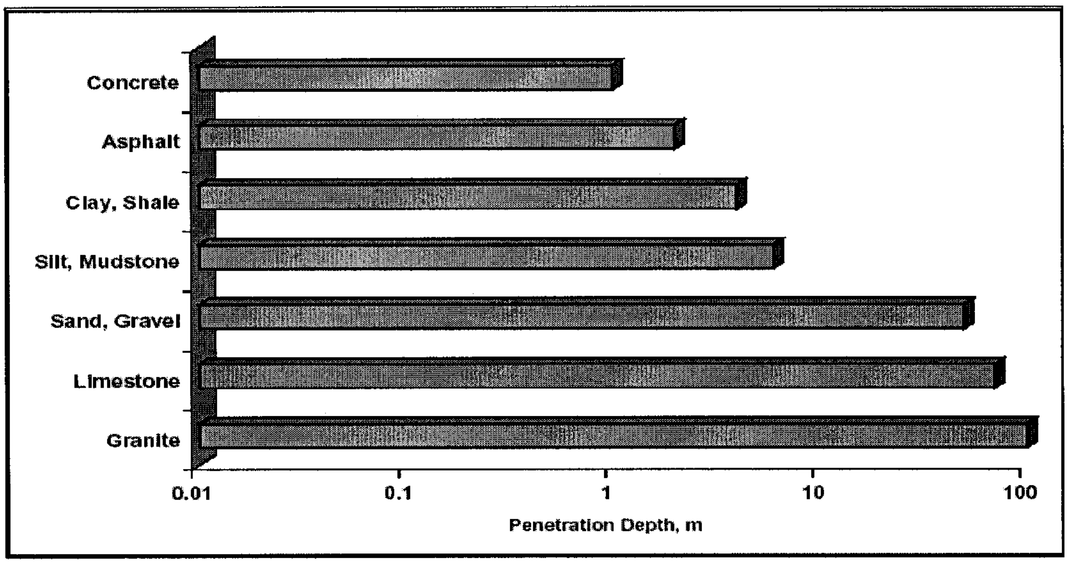

Figure B-5 Typical GPR Exploration Depths (Allouche et al., 2002)

For example, GPR has little effectiveness for soils with high electrical conductivity such as clay soils, because the high conductivity soils will cause severe attenuation of the GPR signals, and hence restricting penetration depth. GPR technique could be combined with sonar and CCTV techniques to detect cavities around sewer pipes, and conjunct with infrared thermography technique (Allouche et al., 2002; Ratliff, 2003).

B.1.8. Ultrasonic Inspection (Sonar)

This technique considered to be alternative to CCTV technique in large diameter pipes or surcharged sewers (Ratliff, 2003). Sonar technique provides a comprehensive condition assessment of the inspected pipe such as pipe-wall deflection, corrosion losses, and cracks/pits in the cross-section of the pipe wall, condition of backfilling, and provide information regarding the volume of debris in the invert (Allouche et al., 2002). In this technique, a sonar inspection device mounted on a crawler unit is placed in the sewer. Ultrasonic signals are sent towards the surface of the object of interest. Then, the ultrasonic signals are reflected from the various surfaces and objects back towards the sonar device. Variations in the amount of energy and the period of time with the reflected signals are used to estimate the location and generate a complete profile of the pipe surface. The profile is presented as a graphic color image, as shown in Figure B-6, each color represent a different reflection (Allouche et al., 2002; Ratliff, 2003).

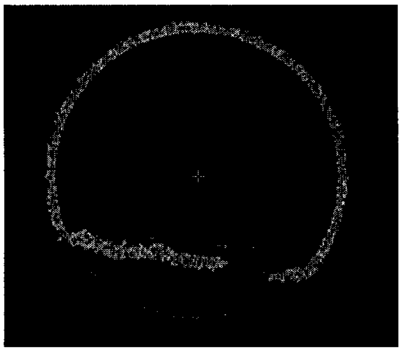

Figure B-6 Sonar generated continuous 360 degree profile of the pipe (Hydromax, 2004)

The accuracy of results varies according to the diameter. For example, when the diameter of the inspected pipe is 200mm, the accuracy has a tolerance of less than 1mm, whereas in larger diameters, the accuracy at 9 ft is approximately 12 mm (Hydromax, 2004).

Ultrasound technique can be used in plastic, concrete and clay pipes that are either filled or empty, but is not well suited to inspect the interior of brick sewers. That is due to the random edges which characterize the brick-mortar interface (Allouche et al., 2002). There are some potential problems in this technique such as missing fine cracks, as fine as 5 mm, defects under normal operations, and blocking or diffusion the ultrasonic signal due to air entrainment and suspended debris in the sewer water (Makar, 1999).

B.1.9. Laser Interferometer

This technique is used to measure the accurate surface profile of pipes three dimensionally, as shown in Figure B-7, and hence identify deflections and other defects such as cracks, joints displacements and debris quantity.

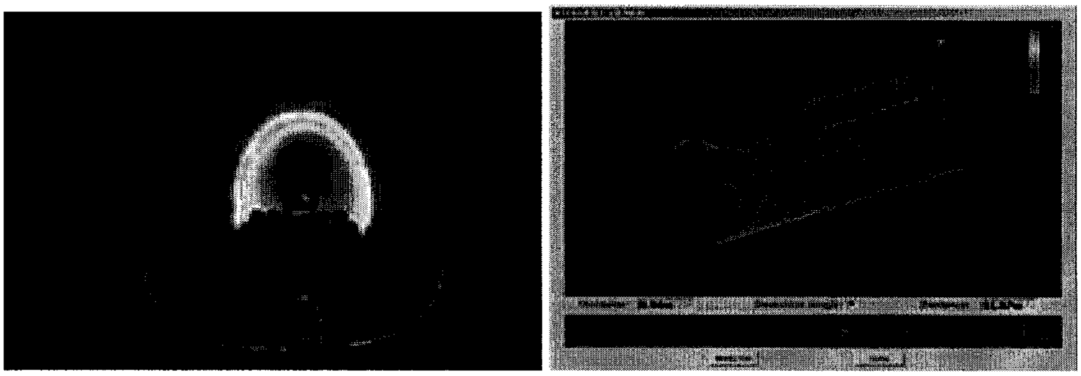

Figure B-7 Laser technique include three- dimensional modeling of the pipelines (Hydromax, 2004).

The process of this technique is fast. It is based on the reflection of light back to the sensor. If the interior pipe wall is smooth, then great amount of light will be reflected, but if it is deflected or cracked, a reduced amount of light will be reflected. Accuracy for laser technique is varies according to pipe diameter, and has a tolerance of 3mm. This technique can only be applied when the inspected pipe is empty or completely full (Allouche et al., 2002; Hydrmax, 2004).

B1.10. Infrared Thermography

This technique considered being effective in detecting leaks and inspecting backfilling surround the pipe. It displays image that use range of intense colors to detect areas of varying temperature. Infrared thermography is a non-contact technique used to inspect large areas from an elevated position above ground (i.e. rooftop of building). Inspection results are displayed and recorded on a monitor that allows both the operator and the engineer to review these results later. If this technique applied in areas congested with other services, the output results can not be analyzed easily. The process of this technique based on measuring any small variations in temperature over a specific area. It produces a thermographic image where objects are represented by their thermal rather than their optical values. Capturing the thermal data, that can be converted by microprocessor to color images for display on a monitor, is done through an infrared scanner head and a detector. The main disadvantages of this technique that it relies heavily on the operator's experience to interpret the results. It, also, can not discover whether the void is a result of soil loss or is avoid in structure. Moreover, it doesn't indicate the size of void. Infrared Thermography technique is easily influenced with the surrounding weather conditions such as rain and snow that tend to mask the heat signature of a leak (Allouche et al., 2002; Ratliff, 2003).

B.1.11. Impulse Hammer

This technique measures and evaluates the structural integrity of brick sewers. The process involves applying a dynamic hammer from a manhole to vibrate and generate a broadband frequency excitation of the walls being tested, and then the dynamic response of the sewer structure is monitored by an accelerometer attached to the structure. The hammer's force input and the accelerometer's output are used to evaluate the structural soundness of the sewer (Allouche et al., 2002).

B.1.12. Impact Echo

It is a method for non destructive testing of sewer pipes. It deploys impact-generated stress sound waves that propagate through sewer and are reflected by internal flows and external surfaces. These waves are then detected by the geophones (Ratliff, 2003; Makar, 1999).

B.1.13 Spectral Analysis of Surface Waves (SASW)

This technique is almost same as impact echo technique, but SAWS technique can inspect both the pipe wall and soil conditions at the same time. It uses more geophones, and separating the waves into different frequency components, which travel at different speeds, and penetrate the soil ahead of the pipe at numerous depths. This technique allows gathering more information about pipe condition and adjacent soil (Ratliff, 2003; Makar, 1999).

B.1.14. Focused Electrode Leak Location (FELL)

The sewer electro-scan or focused electrode leak locator was developed in Germany for identifying potential leaks in sewer system (i.e. joints, cracks, and service connections). FELL system locates defects and leaks within inches, and determines type of defects without cleaning the inspected line. The methodology of inspection is based on placement of an electrode into the ground near pipeline segment.. Then, a sewer jetting hose is passed through the sewer and attached to a sonde, which emits an electric current and a sliding pipe plug. Afterwards, the line is filled to a depth that the joints are completely immersed with water. As the sonde is pulled through the pipeline, the emission of the electric current is recorded digitally and mapped in association with the linear position in pipeline. The output is recorded and displayed digitally on a computer screen in real time as shown in Figure B-8.

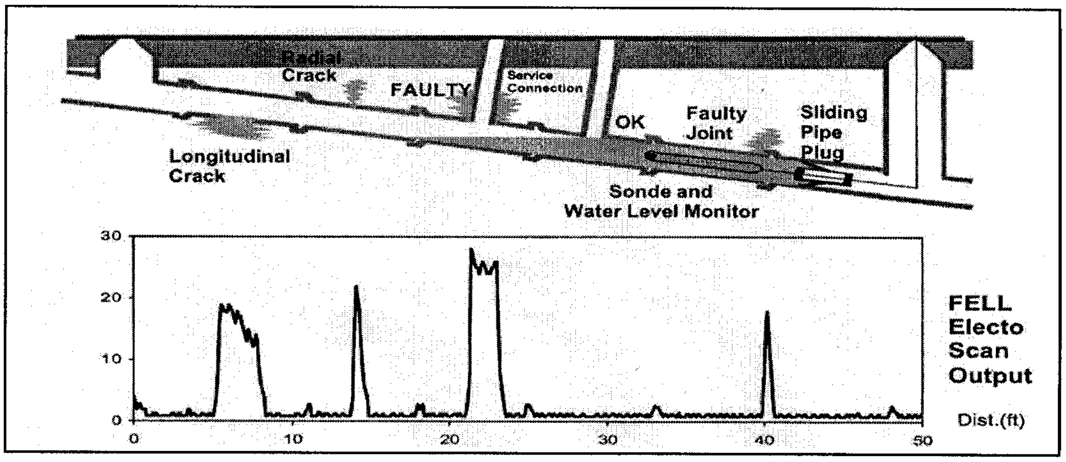

Figure B-8 FELL Schematic & Electric Output I&I at Defects (Adapted from Hydromax, 2004)

FELL inspection system provides a cost-effective, first-step technique for locating and identifying leaks in reinforced concrete, clay, brick, plastic, or plastic lined steel pipe (Ratliff, 2003; Hydromax, 2004).

B.1.15. MAKRO

This technique is not commercially available; it is a self-directed sewer robot inspection system, which is used to robotically detect type, location, and size of defects in sewer lines. It is developed to be operated autonomously in sewer pipes of 300-600 mm diameter. MAKRO has a snake movement, so it overturns all obstacles by moving up and down, or turns left or right, as shown in Figure B-9. It is utilized with an ultrasound sensor that detects obstacles that are blocking the pipe, and ultrasonic sensors that measures cracks and wall thickness. MAKRO is able to detect damages up to 10 cm behind the pipe wall, leakage holes in surrounding soils, and cracks in the pipe walls. The robot motion and sensor functions are controlled and monitored by an operator in the mobile control and observation station; however, a human operator can, but need not, involved in control the robot. (Ratliff, 2003; MAKRO 2000).

Figure B-9 MAKRO Sewer Robot

B.1.16. Pipe Inspection Rapid Assessment Technique (PIRAT)

The PIRAT sewer inspection system has been developed between 1993 and 1996, as shown in Figure A-10. This technique, also, not commercially available at this time, but it provides advanced options for inspection. PIRAT system utilizes a combination of robotics, machine vision, and artificial intelligence to robotically investigate and assess sewer lines. It utilizes laser and sonar scanners which is tele-operated from a supervision unit through a 250 m cable by a human operator. However, PIRAT system is deployed only in pipes with 600mm diameter or larger, and cannot perform turns at pipe junctions. (Ratliff, 2003; Shehab-Eldeen, 2001; PIRAT, 2004).

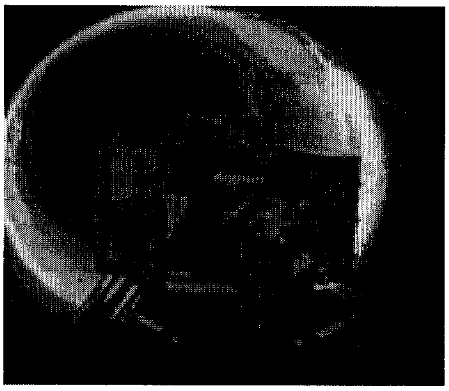

Figure B-10 PIRAT Sewer Robot (Adapted from PIRAT, 2004)

B.2. Methods Used for the Condition Assessment of Lining for Tunnels

Lining inspection is carried out in order to gather more information on tunnel condition. There are different approaches that allow for a definitive assessment of tunnel lining as follows (Locatelli et al., 2001):

B.2.1. Visual and Hammering Inspection

In this technique a hydraulic platform is used bridging the tunnel width. Two or three inspectors strike the surface with hammers to identify acoustically where concrete is unsound. This technique can inspect the liner up to 20-30 cm.

B.2.2. Destructive method

This technique allows measuring lining depth and void depth between lining and rock. A group of five radial holes samples is drilled where voids are expected. Then, the samples are analyzed according to compression resistance and to degree of carbonation.

B.2.3 Ground Penetrating Radar (GPR)

It is considered as a powerful tool to detect the voids above the lining on a continuous basis. Technique methodology is explained earlier.

B.2.4 Laser scanner

This technique is used to record high digital resolution visible and infrared images of the inner tunnel lining. The inner lining of the tunnel is scanned by a two channel laser mounted on a horizontal axis. The recorded visible and infrared pictures are analyzed to detect cracks, defects, cavities and water leakage (Naumann et al., 2003).

B.3. Methods Used for the Condition Assessment of Highway Structures

(Naumann et al., 2003) present the different non-destructive techniques that can be used to assess Highway structures (bridges, highways, etc.), most of these techniques described earlier, as follows:

B.3.1. Visual Testing

It is the most common application of NDT. Technique methodology is explained earlier.

B.3.2. Hammering Inspection

This technique is used to detect concrete strength, concrete cover, and delaminations.

B.3.3. Ground penetrating radar (GPR)

This technique is used for investigation of the structural composition up to one meter such as the case in bridges. Moreover, it is used to locate reinforcement in concrete and build-in objects such as connectors or anchors. Also, it is used to detect damaged and defected areas (Naumann et al., 2003). GPR has, also, been employed to assess the conditions of the railway track substructure (i.e. ballast, subballast, and subgrade), and to produce quantitative indices of substructure condition (Selig et al., 2003)

B.3.4. Ultrasonic Devices

Ultrasonic testing method can be used both to determine metal thickness and to detect internal flaws. Technique methodology is explained earlier.

B.3.5. Magnetic Flux technique

This technique used to inspect and detect ruptures in reinforcement of concrete, tendons, or wires in a cable. Technique methodology is explained earlier.

B.3.6. Radiography

Radiography (X-ray) technique is used to determine variation in metal thickness, and detect certain types of internal voids and inclusions. Technique methodology is explained earlier.

B.3.7. Acoustic Test Methods

This technique is based on acoustic wave transmission properties. When energy is released (i.e. high-tensile wire failures, or concrete cracks), waves spread in structure materials. Acoustic sensors are distributed along structure to detect and record released signals, as shown in Figure B-11.

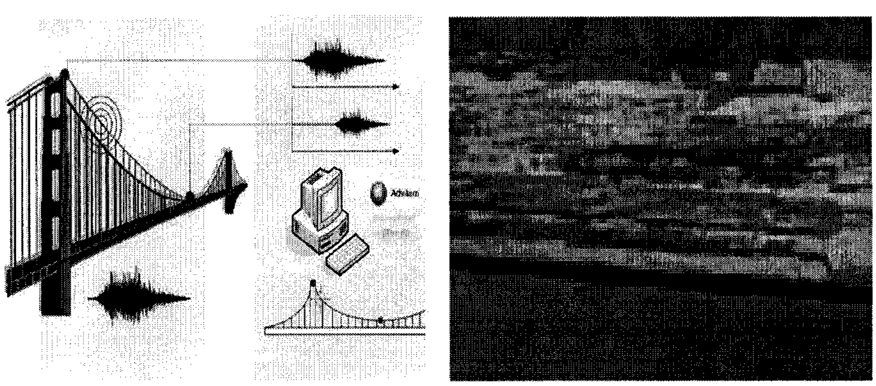

Figure B-11 Acoustic Test Method for Bridge (Advitam-Group, 2004b)

Computation of signal locates the place of defect. Another type of the acoustic technique is the Impact-Echo. It is used effectively for testing and detecting defects in concrete structures of thickness up to 1 meter. Impact-Echo technique introduces a stress pulse into the structure at the accessible surface. The propagated pulse is reflected by defects, cavities, or the interface to other materials. The surface displacements caused by the reflected signal are recorded and transformed into the frequency domain. Then, the signal amplitude versus the frequency is plotted according to results.

B.4. Methods Used for the Condition Assessment of Natural Gas Pipelines:

(Bickerstaff et al., 2003) present a review for In-line Inspection of Natural Gas Pipelines. There are different sensor technologies (NDT) that can be used to asses the condition of the natural gas pipelines, some of these techniques described earlier, as follows:

B.4.1. Eddy Current Testing (ET)

It is an electromagnetic technique that can only be used on conductive materials. It is applied to detect cracks, defects, variation in size or in material. Technique methodology is explained earlier.

B.4.2. Ultrasonic Inspection

This technique is successfully used to detect defects or measure material thickness, by applying sound waves of short wavelength and high frequency to the pipe. Technique methodology is explained earlier.

B.4.3. Magnetic flux leakage (MFL)

It is the most common technology used in in-line inspection. MFL locates oil or gas pipeline defects. A saturating magnetic field, supplied by huge magnets, as shown in Figure B-12, is applied into the pipe, by applying a saturating magnetic field, then by using sensors the changes in the applied magnetic field is measured and recorded.

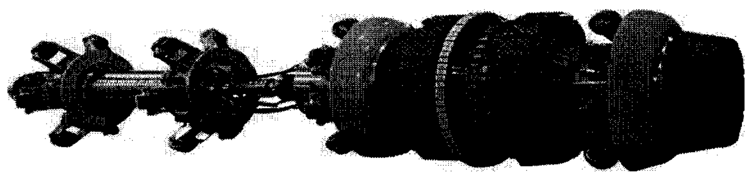

Figure B-12 A typical MFL pig (Bickerstaff et al., 2003)

B.4.4. Electromagnetic Acoustic Transducer (EMAT)

Application of EMATs for use is still in the developmental phase. The EMAT consists of a coil in a magnetic field at the internal surface of the pipe wall. Alternating current placed through the coil induces a current in the pipe wall, causing Lorentz forces (force acting on moving charges in magnetic fields), which in turn generate ultrasound. The type and the configuration of the transducer used define the types and modes of generated ultrasound and the characteristics of its propagation through the pipe wall.

B.4.5. Acoustic Emission (AE)

This technique involves permanently attaching one or more ultrasonic transducers to the object, and analyzing the sounds generated or induced into the system through computer based instruments. This method of inspection is not associated with pigging, but rather is an effort to monitor pipeline conditions without the use of a pig.

APPEDIX (C)

APPENDIX (C)

SAMPLE EXPERT SURVEY QUESTIONAIRE

CONDITION ASSESSMENT FOR WATER MAINS

Several factors may play a role in water mains deterioration. These factors could be physical, environmental, or operational. The identification of effect and weight of these factors on water mains deterioration is crucial because it can be used as a base to rate the existing condition of water mains. Consequently, it will assist engineers in prioritizing pipe inspection and rehabilitation planning of their existing water mains.

We believe that your judgment and expertise in filling the following table, "The pair-wise comparison matrix between the proposed factors", will help us classify and identify the main factors, and their weights, which lead to water main deterioration. The knowledge base gathered from a number of experts like you will be integrated to propose a condition rating scale and condition rating model for water mains.

Supervisor,

Tarek Zayed, Ph.D., P.E.

Assistant Professor

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Tel.: (514) 848-2424 ext. 8779
Fax: (514) 848-7965
Email: zayed@bcee.concordia.ca

Return Information: Please, return this questionnaire to ***Hassan Al Barqawi*** Research Assistant, Department of Building, Civil & Environmental Engineering, Concordia University	Tel.: (450) 672-0452 E-mail: ha_albar@alcor.concordia.ca hassanbarqawi@yahoo.com (preferred)

I. COMPANY INFORMATION:

This part of information is very confidential and not for public use. It is required to distinguish only between client and consultant company categories.

I.1 Municipality/Company: ______________________

I.2 Check your company's classification:

a. Client : _______ b. Consultant : _______

I.3 Your information :

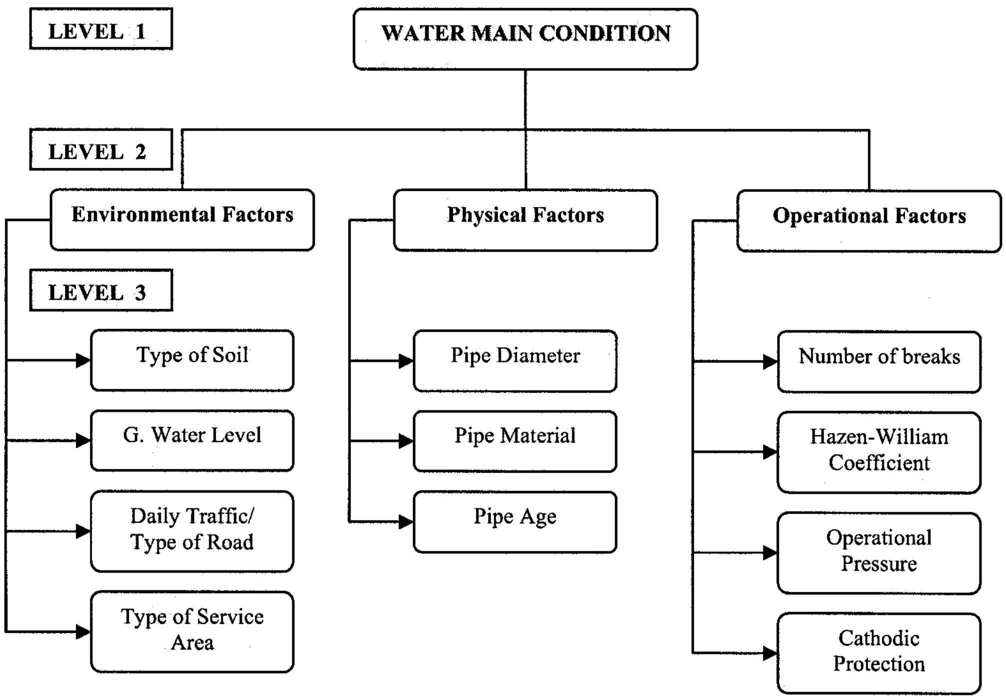
Name:	
Position:	
E.mail:	
Phone:	
Fax:	

II. PAIR-WISE COMPARISON BETWEEN DIFFERENT FACTORS THAT AFFECT CONDITION OF WATER MAINS:

II .1 Main Factors that Affect Water Mains Condition:

Please, try to provide us with your evaluation to the factors that affect Water Mains Condition. The following list of factors is the list that is suggested by us. If you have any factors that you would like to add or cancel, please, feel free to add them in the available blank areas. These factors are:

1- Type of Pipe.	**2- Diameter of Pipe.**
3- Age/ Year of Installation.	**4- Breakage Rate.**
5- Hazen-William Coefficient.	**6- Working Pressure .**
7- Type of Soil.(Aggressive, Moderate, Non Aggressive,...)	**8- Type of Service (Commercial, Residential, Industrial).**
9- Ground Water Level (High, Low, Non).	**10- Daily Traffic/Type of Road.**
11- Cathodic Protection (For Cast and Ductile Iron Pipes).	



II .2 Pair-wise Comparison between Factors that Affects Condition of Water Mains:

Please, try to make a comparison between each factor and the other factors based on your evaluation to the importance of this factor over the other. In other words, compare the importance of each factor against each of the other factors individually. This importance is evaluated regarding its effect on Condition Assessment.

The following tables show the pair-wise comparison matrix among the different factors affecting the condition of water mains based upon the proposed hierarchy (levels). For example, if the breakage rate is 3 times more important than the working pressure in affecting the condition of the water mains, just put 3 in the intersection cell of the breakage rate row with the working pressure column. In contrast, the intersection cell between the working pressure row and the breakage rate column will be the reverse (1/3). Please, do so for all the factors against each other to fill all the cells of the matrix. It is clear that comparing the factor to itself should be 1 as indicated in the diagonal of the matrix. The matrix is as follows:

II.2.1. **Main factors pair-wise comparison matrix**:

Factors	***Environmental***	***Physical***	***Operational***
Environmental	1		
Physical		1	
Operational			1

II.2.2. **Environmental' sub-factors pair-wise comparison matrix**:

Sub-Factors	**Type of Soil**	**Ground Water Level**	**Daily Traffic/ Type of Road**	**Type of Serviced Area**
Type of Soil	1			
Ground Water Level		1		
Daily Traffic/ Type of Road			1	
Type of Serviced Area				1

II.2.3. **Physical' sub-factors pair-wise comparison matrix**

Sub- Factors	***Pipe Material***	***Pipe Diameter***	***Pipe Age***
Pipe Material	1		
Pipe Diameter		1	
Pipe Age			1

II.2.4. **Operational' sub-factors pair-wise comparison matrix**:

Sub-Factors	**No. of Breaks**	**Hazen-William Coefficient**	**Operational Pressure**	**Cathodic protection**
No. of Breaks	1			
C-Factor		1		
Operational Pressure			1	
Cathodic protection				1

III. Scaling Parameters

In order to be able to deploy the resultant weight of each factor, scale should be assigned to each parameter so we would be able to predict the condition rating of existing pipes. The following section describes the suggested scale by other expertise, scaled (0 to 10), ("0"represent the lowest scale value, and "10" represent the highest scale value).

Please feel free to modify it according to your experience so we would be able to develop a reliable model.

III.1 Physical Factors

IV.1.1 *Type of Pipe*

Cast Iron (Installed Before the WW)	10
Cast Iron (Installed After the WW)	6
Ductile Iron	8
Asbestos	8
Concrete Pipes	8
PVC	9
Polyethylene Pipes	10

III.1.2 *Pipe Diameter*

Less or equal 100mm	5
150mm, and 200mm	7
250mm, and 300mm	8
350mm, 400mm, and 450mm	9
Greater or equal 500mm	10

III.1.3 *Pipe Age*

Greater than 90 yrs	0
90 yrs $\geq$ Age $\geq$ 80 yrs	1
80 yrs $\geq$ Age $\geq$ 70 yrs	2
70 yrs $\geq$ Age $\geq$ 60 yrs	3
60 yrs $\geq$ Age $\geq$ 40 yrs	5
40 yrs $\geq$ Age $\geq$ 30 yrs	7
30 yrs $\geq$ Age $\geq$ 20 yrs	8

20 yrs ≥ Age ≥ 10 yrs	9
Less than 10 yrs	10

III.2 Environmental Factors

III.2.1 *Type of Soil*	
Highly aggressive	0
Aggressive	5
Moderate	7
Non-Aggressive	10
III.2.2 *Ground Water Level*	
High	3
Moderate	7
Low	10
III.2.3 *Type of Service*	
Industrial	10
Commercial	8
Residential	8
Rural (Transmission)	10
III.2.4.a. *Average Daily Traffic*	
Heavy	6
Moderate	8
Low	10
III.2.4.b. *Type of Road*	
Local	8
Primary	6
Secondary	10
Free way	5
Arterial	5
III.2.4.c. *Type of Surface*	
Asphalt	5
Seal	7.5

Foot path	7.5
Unpaved	10

III.3 Operational Factors

III.3.1 *Number of Break*

Greater than 2 Breaks/km/yr	0
2.0 ≥ Breakage rate ≥ 1.0	1
1.0 ≥ Breakage rate ≥ 0.5	2
0.5 ≥ Breakage rate ≥ 0.2	4
0.2 ≥ Breakage rate ≥ 0.1	6
0.1 ≥ Breakage rate ≥ 0.05	8
Less than 0.05 Breaks/km/yr	10

III.3.2 *Hazen-William Coefficient*

Greater than 101	10
101 ≥ C-Factor ≥ 81	8
81 ≥ C-Factor ≥ 61	6
61 ≥ C-Factor ≥ 41	4
Less than 41	2

III.3.3 *Cathodic Protection*

Cathodic Protection Applied	10
Cathodic Protection NOT Applied	6

III.3.4 *Operational Pressure*

High	7
Moderate	10
Low	10

IV. CONDITION RATING SCALE (0 - 10):

We are planning to develop a condition rating scale for water mains from 0 to 10. But we need your judgment to assist us in building criteria for scaling, and actions required. For example, if the condition of the pipe is in between 9 - 10, means the water means are in excellent condition and no need to take any action.

Scale	Criteria	Action
Ex.: 9 – 10 (Excellent)	Newly /Recently installed	No action required
8 – 9 (V. Good)	Like new with no signs of corrosion or deterioration	Re-assess in 15 years.

(Note: Criteria could be Excellent, V. Good, Good, Moderate, Bad, Poor, Critical, Very Bad or anything else suggested by you. Also, Actions could be no action required at this time, need flushing, need inspection, need lining, rehabilitation required, replacement needed....etc, or anything else suggested by you)

V. ADDITIONAL COMMENTS:

APPEDIX (D)

APPENDIX (D)

D1. NEUROSHELL SCHEMA

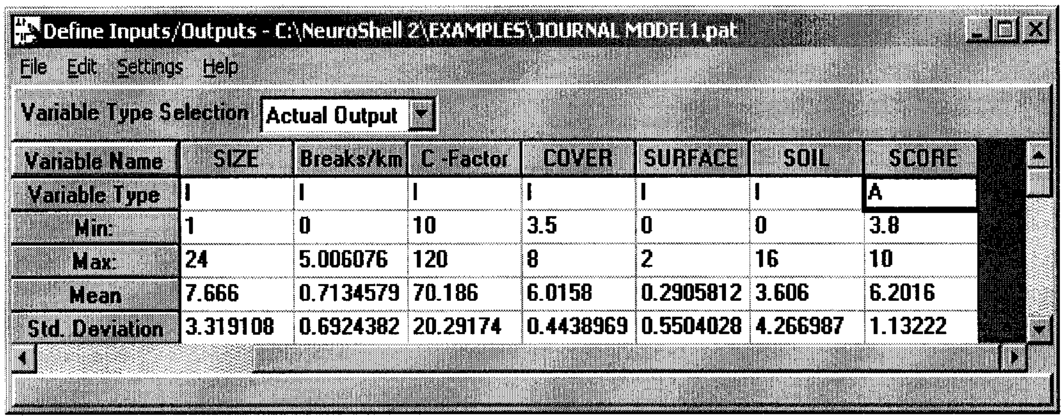


Figure D-1 Neuroshell Schema; Selection of Input and Output Variables

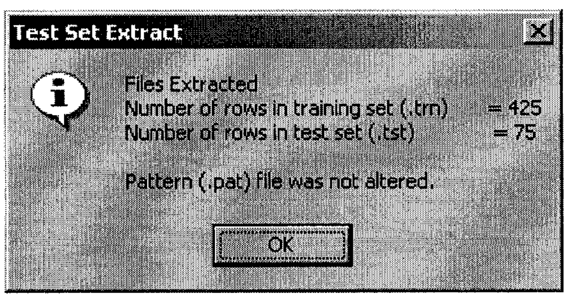


Figure D-2 Neuroshell Schema; Test Set Extraction

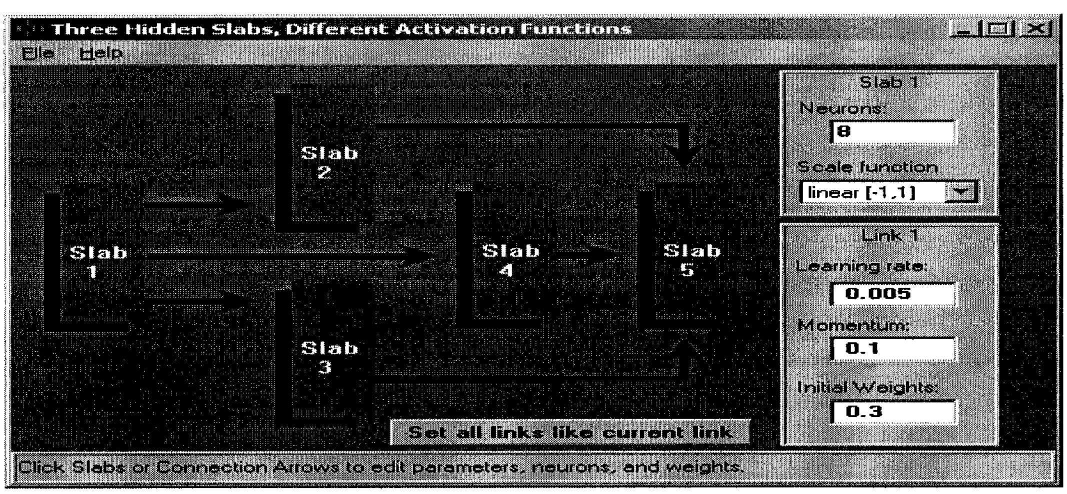


Figure D-3 Neuroshell Schema; BPNN Design Structure

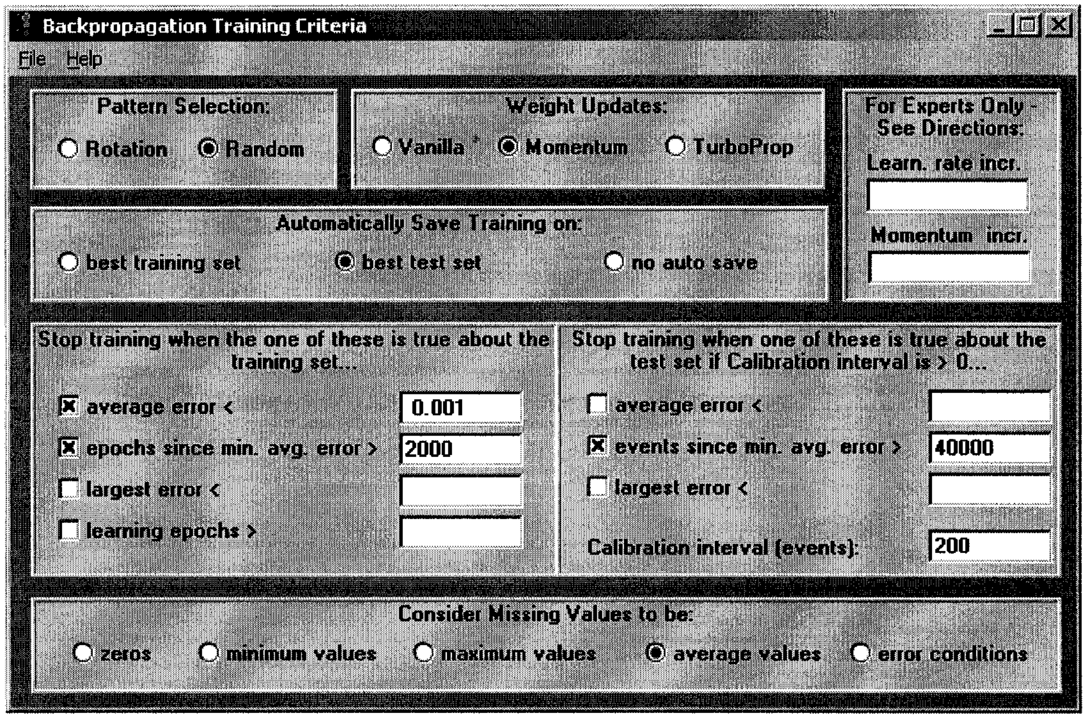


Figure D-4 Neuroshell Schema; BPNN Training Criteria

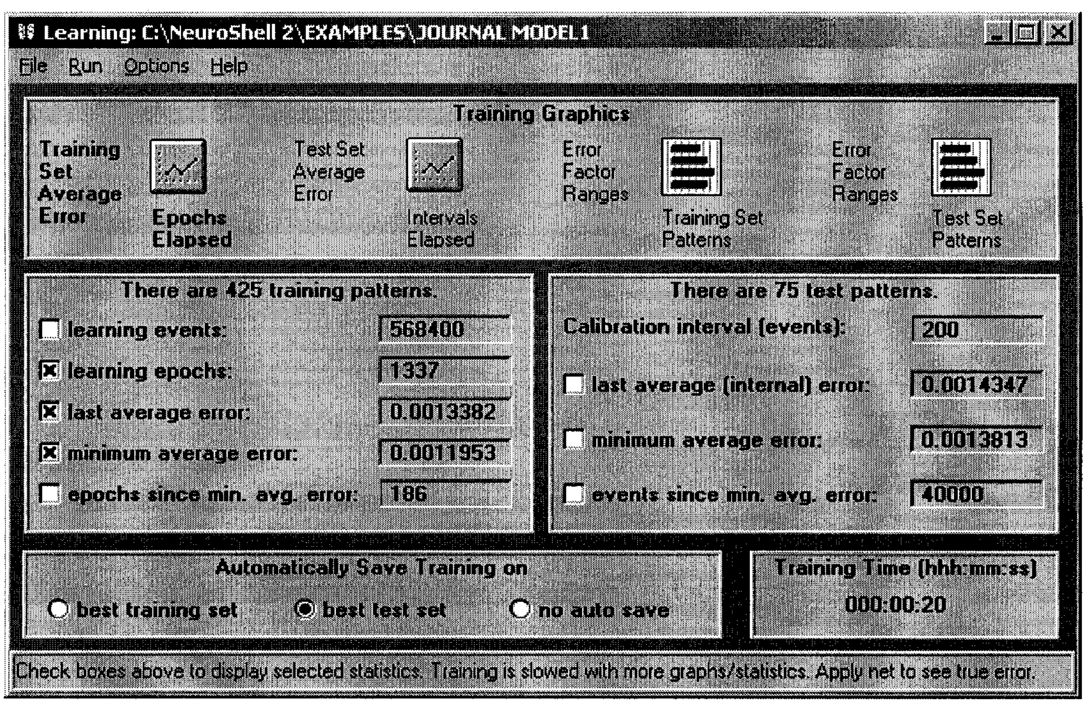


Figure D-5 Neuroshell Schema; Training and Testing Results

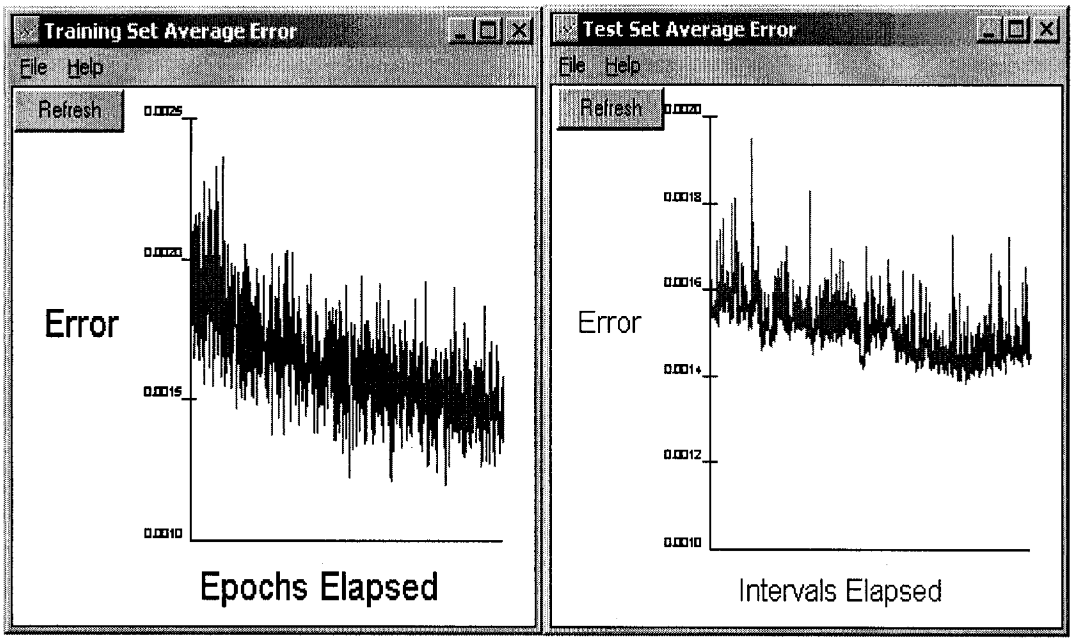


Figure D-6 Neuroshell Schema; Training and Testing Average Error

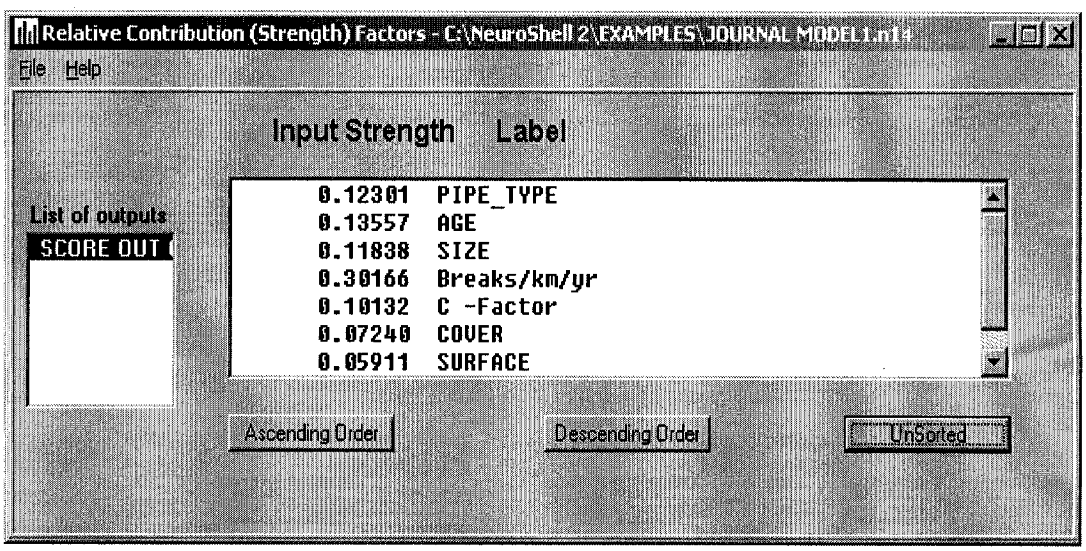


Figure D-7 Neuroshell Schema; Relative Weight Input Factors Contribution Factors

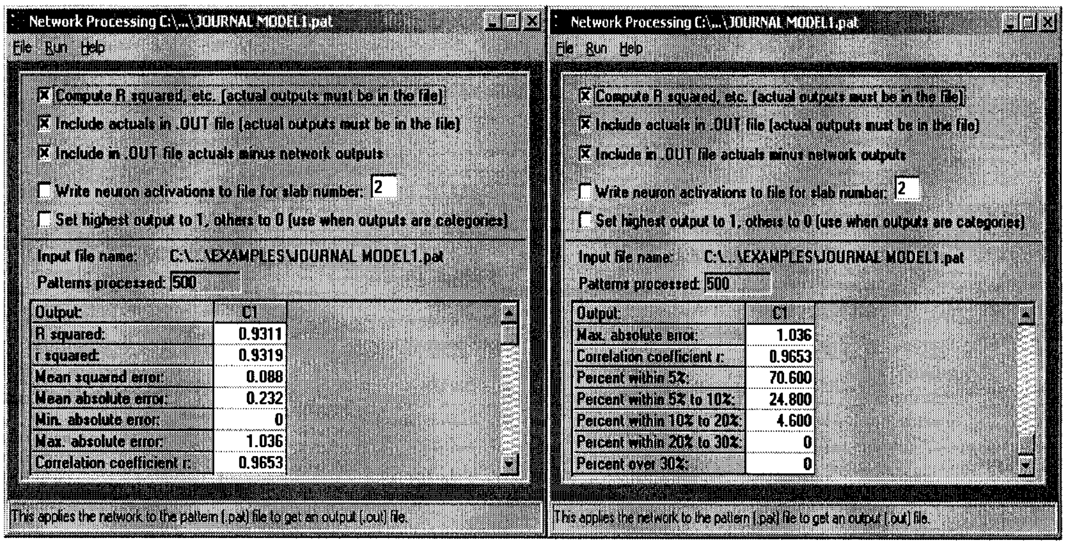


Figure D-8 Neuroshell Schema; Model Results

D2. VALIDATION RESULTS FOR ANN

Table D-1 Validation Results

No.	Actual (1)	Network (1)	Act-Net (1)	Actual Diff.	% of Differ.	(AIP)	(AVP)	Absolute (Act. - Pred.)	(Act.-Pred.)2
1	5.8000	5.9825	0.9175	0.1825	3.1469	0.0305	0.9695	0.1825	0.0333
2	5.4000	5.1431	1.7569	-0.2569	4.7582	0.0500	0.9500	0.2569	0.0660
3	6.8000	7.0892	-0.1892	0.2892	4.2533	0.0408	0.9592	0.2892	0.0837
4	5.8000	5.9863	0.9137	0.1863	3.2114	0.0311	0.9689	0.1863	0.0347
5	5.6000	5.5093	1.3907	-0.0907	1.6201	0.0165	0.9835	0.0907	0.0082
6	5.6000	4.8920	2.0080	-0.7080	12.6431	0.1447	0.8553	0.7080	0.5013
7	5.0000	5.1586	1.7414	0.1586	3.1716	0.0307	0.9693	0.1586	0.0251
8	6.4000	6.6148	0.2852	0.2148	3.3563	0.0325	0.9675	0.2148	0.0461
9	5.2000	5.2570	1.6430	0.0570	1.0954	0.0108	0.9892	0.0570	0.0032
10	5.4000	5.1431	1.7569	-0.2569	4.7582	0.0500	0.9500	0.2569	0.0660
11	6.8000	7.0892	-0.1892	0.2892	4.2533	0.0408	0.9592	0.2892	0.0837
12	7.0000	7.4042	-0.5042	0.4042	5.7744	0.0546	0.9454	0.4042	0.1634
13	7.6000	7.7984	-0.8984	0.1984	2.6103	0.0254	0.9746	0.1984	0.0394
14	7.2000	7.9771	-1.0771	0.7771	10.7927	0.0974	0.9026	0.7771	0.6038
15	5.0000	4.7262	2.1738	-0.2738	5.4767	0.0579	0.9421	0.2738	0.0750
16	5.8000	5.8753	1.0247	0.0753	1.2989	0.0128	0.9872	0.0753	0.0057
17	6.4000	6.1551	0.7449	-0.2449	3.8261	0.0398	0.9602	0.2449	0.0600
18	7.0000	6.8352	0.0648	-0.1648	2.3544	0.0241	0.9759	0.1648	0.0272
19	7.4000	7.1946	-0.2946	-0.2054	2.7759	0.0286	0.9714	0.2054	0.0422
20	6.8000	6.4950	0.4050	-0.3050	4.4850	0.0470	0.9530	0.3050	0.0930
21	5.4000	5.4229	1.4771	0.0229	0.4233	0.0042	0.9958	0.0229	0.0005
22	5.4000	5.5641	1.3359	0.1641	3.0392	0.0295	0.9705	0.1641	0.0269
23	5.6000	5.5009	1.3991	-0.0991	1.7693	0.0180	0.9820	0.0991	0.0098
24	7.0000	6.8352	0.0648	-0.1648	2.3544	0.0241	0.9759	0.1648	0.0272
25	6.2000	6.8328	0.0672	0.6328	10.2064	0.0926	0.9074	0.6328	0.4004
26	6.8000	7.0053	-0.1053	0.2053	3.0194	0.0293	0.9707	0.2053	0.0422
27	6.6000	6.4943	0.4057	-0.1057	1.6014	0.0163	0.9837	0.1057	0.0112
28	6.8000	7.5525	-0.6525	0.7525	11.0662	0.0996	0.9004	0.7525	0.5663
29	5.6000	4.9391	1.9609	-0.6609	11.8022	0.1338	0.8662	0.6609	0.4368
30	7.2000	6.8216	0.0784	-0.3784	5.2549	0.0555	0.9445	0.3784	0.1431
31	6.8000	6.9009	-0.0009	0.1009	1.4838	0.0146	0.9854	0.1009	0.0102
32	6.0000	6.0473	0.8527	0.0473	0.7885	0.0078	0.9922	0.0473	0.0022
33	6.2000	6.8251	0.0749	0.6251	10.0821	0.0916	0.9084	0.6251	0.3907
34	5.8000	6.0941	0.8059	0.2941	5.0700	0.0483	0.9517	0.2941	0.0865
35	5.8000	6.0898	0.8102	0.2898	4.9970	0.0476	0.9524	0.2898	0.0840
36	6.6000	6.5906	0.3094	-0.0094	0.1430	0.0014	0.9986	0.0094	0.0001
37	6.0000	5.5724	1.3276	-0.4276	7.1269	0.0767	0.9233	0.4276	0.1829
38	6.8000	6.4444	0.4556	-0.3556	5.2291	0.0552	0.9448	0.3556	0.1264
39	5.6000	5.7447	1.1553	0.1447	2.5835	0.0252	0.9748	0.1447	0.0209
40	7.6000	7.3577	-0.4577	-0.2423	3.1876	0.0329	0.9671	0.2423	0.0587
41	7.6000	7.7531	-0.8531	0.1531	2.0139	0.0197	0.9803	0.1531	0.0234
42	5.2000	5.6077	1.2923	0.4077	7.8409	0.0727	0.9273	0.4077	0.1662
43	5.8000	6.0941	0.8059	0.2941	5.0700	0.0483	0.9517	0.2941	0.0865
44	8.8000	8.4759	-1.5759	-0.3241	3.6835	0.0382	0.9618	0.3241	0.1051
45	6.6000	6.8800	0.0200	0.2800	4.2429	0.0407	0.9593	0.2800	0.0784
46	6.8000	6.9589	-0.0589	0.1589	2.3365	0.0228	0.9772	0.1589	0.0252
47	7.0000	7.1846	-0.2846	0.1846	2.6376	0.0257	0.9743	0.1846	0.0341
48	7.2000	7.3781	-0.4781	0.1781	2.4736	0.0241	0.9759	0.1781	0.0317
49	6.6000	6.4731	0.4269	-0.1269	1.9234	0.0196	0.9804	0.1269	0.0161
50	8.2000	7.9657	-1.0657	-0.2343	2.8568	0.0294	0.9706	0.2343	0.0549
51	7.4000	7.3427	-0.4427	-0.0573	0.7745	0.0078	0.9922	0.0573	0.0033
52	10.0000	9.3192	-2.4192	-0.6808	6.8078	0.0731	0.9269	0.6808	0.4635
53	5.8000	6.3794	0.5206	0.5794	9.9902	0.0908	0.9092	0.5794	0.3357
54	4.6000	4.5980	2.3020	-0.0020	0.0443	0.0004	0.9996	0.0020	0.0000
55	8.2000	7.9681	-1.0681	-0.2319	2.8279	0.0291	0.9709	0.2319	0.0538
56	8.4000	8.2484	-1.3484	-0.1516	1.8053	0.0184	0.9816	0.1516	0.0230
57	8.8000	7.9120	-1.0120	-0.8880	10.0914	0.1122	0.8878	0.8880	0.7886
58	8.2000	7.7516	-0.8516	-0.4484	5.4680	0.0578	0.9422	0.4484	0.2010
59	7.6000	7.5467	-0.6467	-0.0533	0.7019	0.0071	0.9929	0.0533	0.0028
60	7.8000	7.4423	-0.5423	-0.3577	4.5856	0.0481	0.9519	0.3577	0.1279
					Total =	2.5564	57.44	16.8547	7.3094

AIP = 0.0426

AVP = 0.9574

Root Mean Square Error (RMS) = 0.0451

Mean Absolute Error (MAE) = 0.2809

APPEDIX (E)

APPENDIX (E)

E.1. DUCTILE IRON PREDICTION CURVES

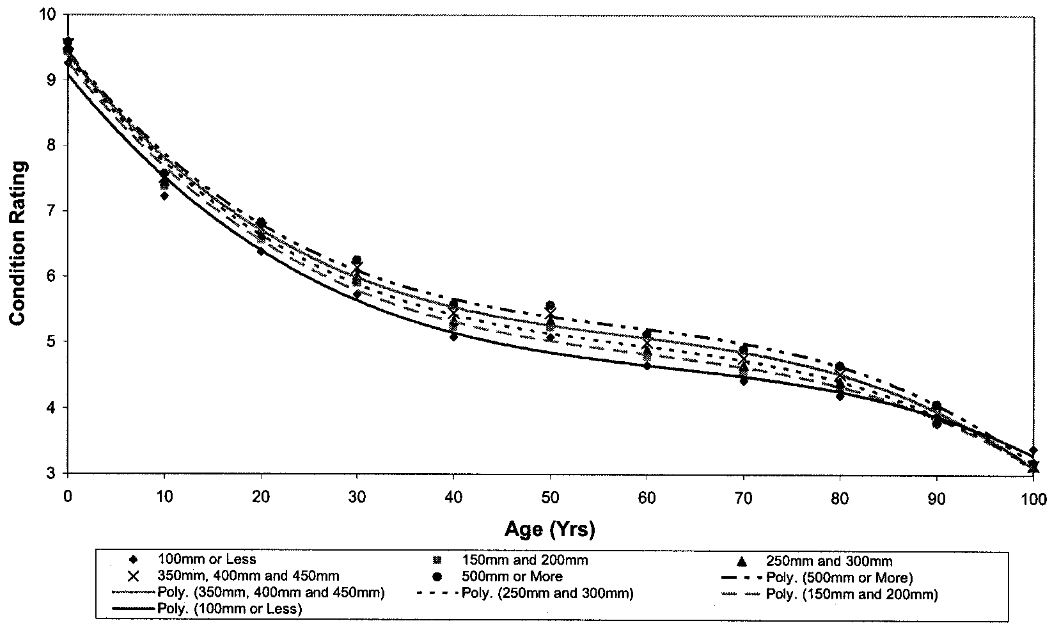


Figure E-1 DI: C-factor (120) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

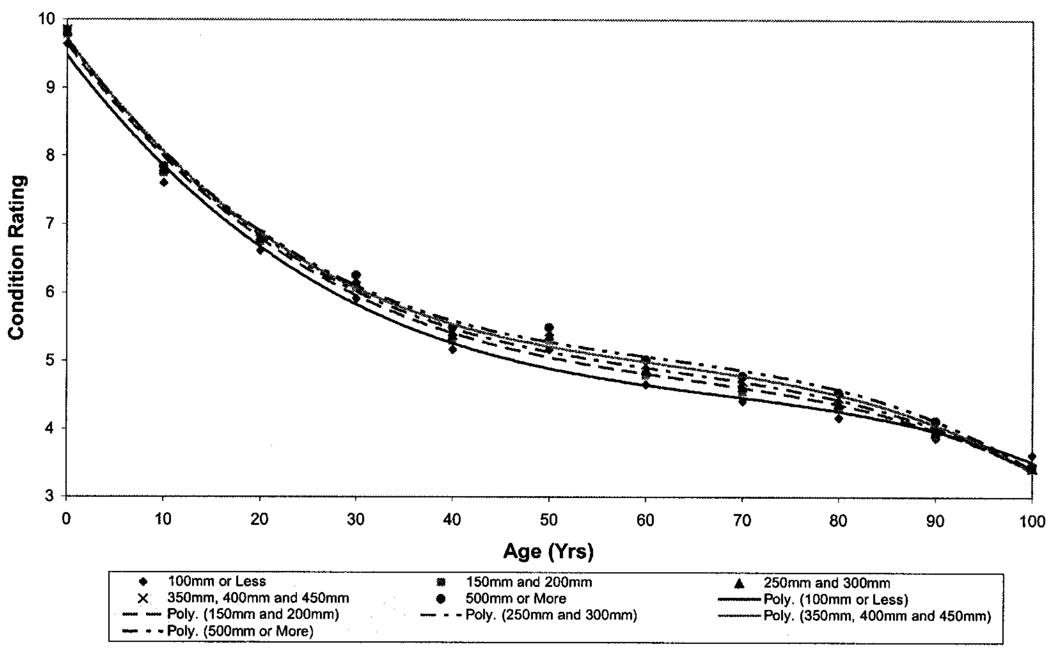


Figure E-2 DI: C-factor (80) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

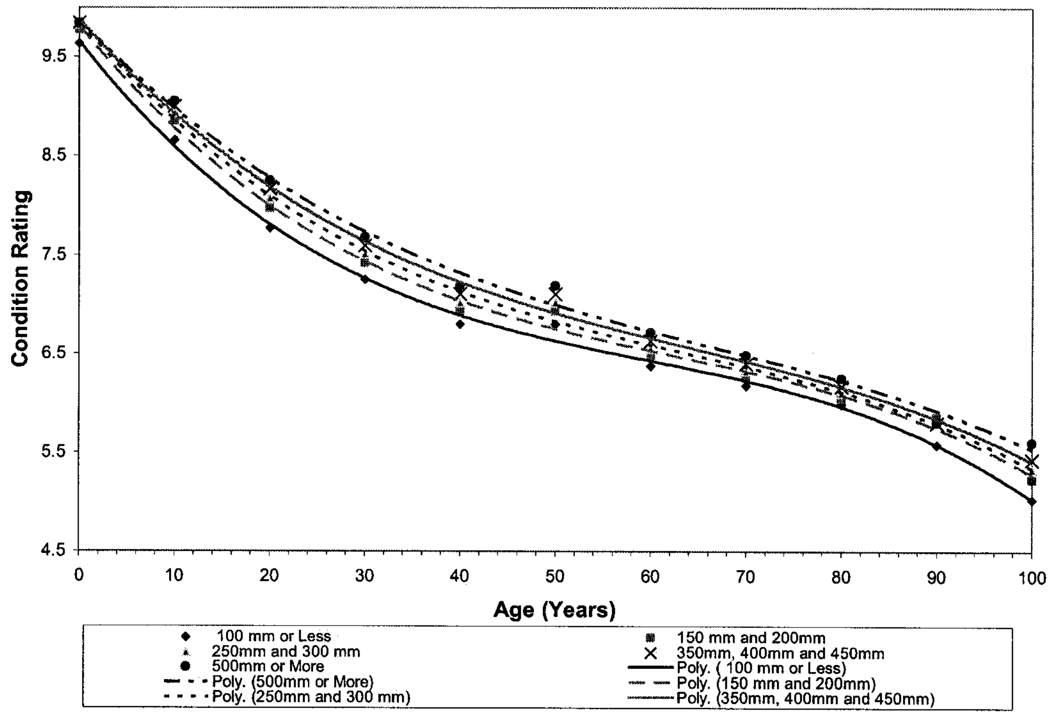


Figure E-3 DI: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate(0.1)

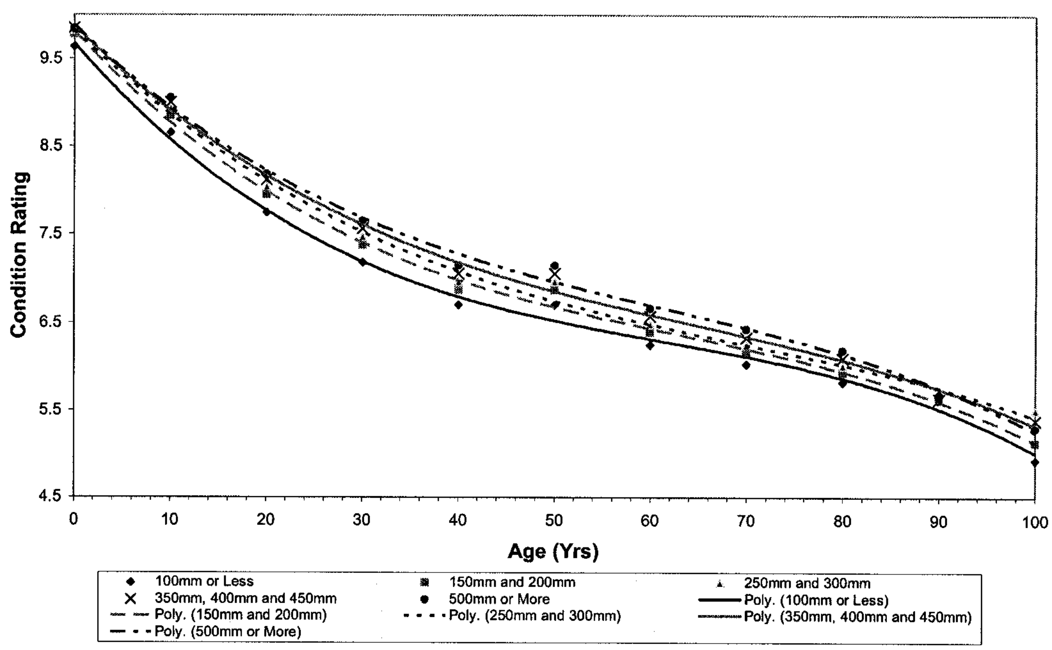


Figure E-4 DI: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Clay) -Breakage Rate (0.1)

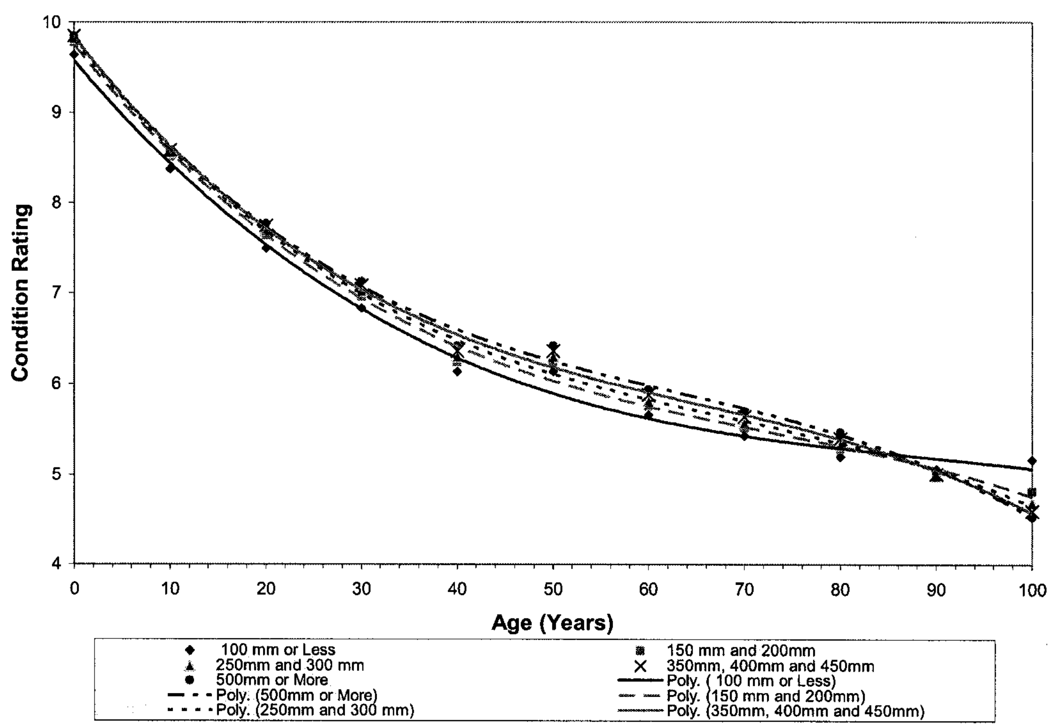


Figure E-5 DI: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

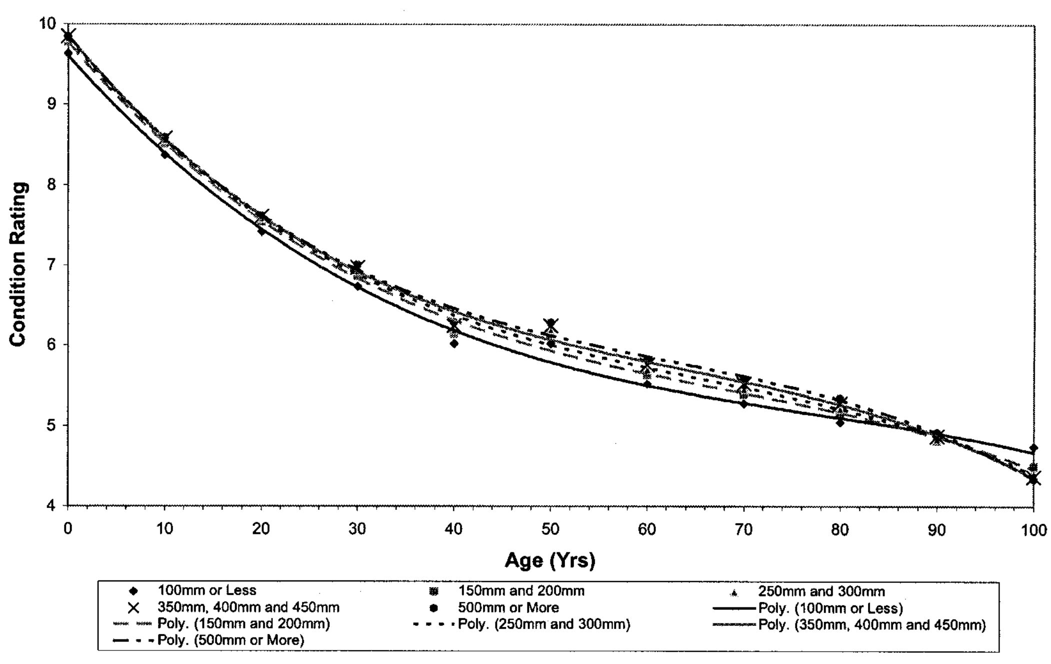


Figure E-6 DI: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

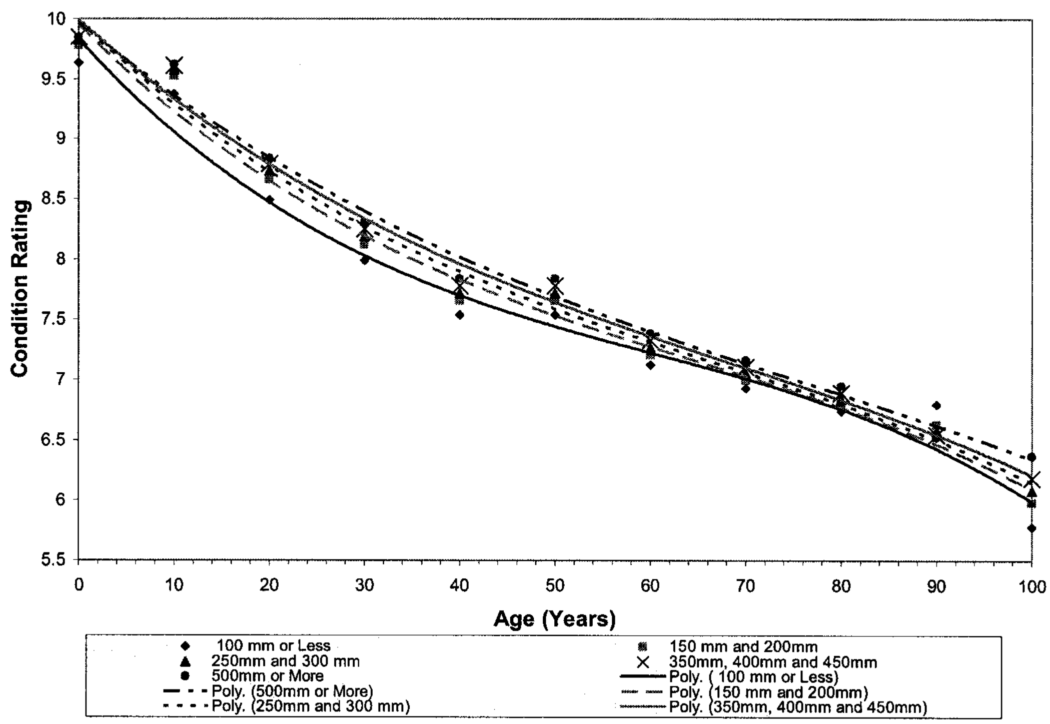


Figure E-7 DI: C-factor (120) - Cathodic Protection (Yes)- Soil Type (Sand) - Breakage Rate (0.1)

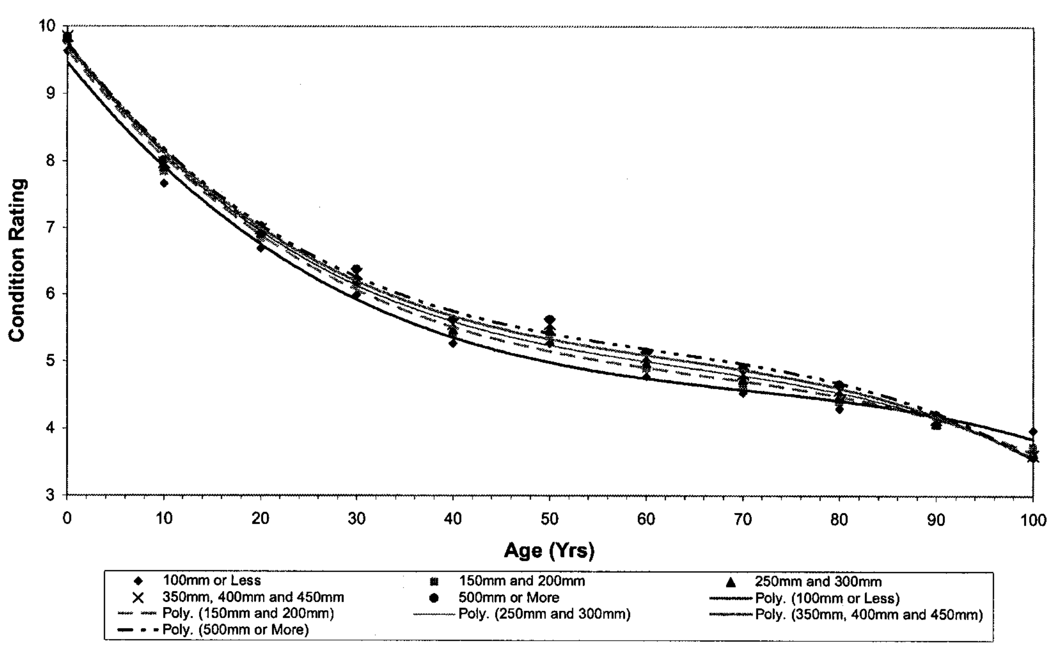


Figure E-8 DI: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

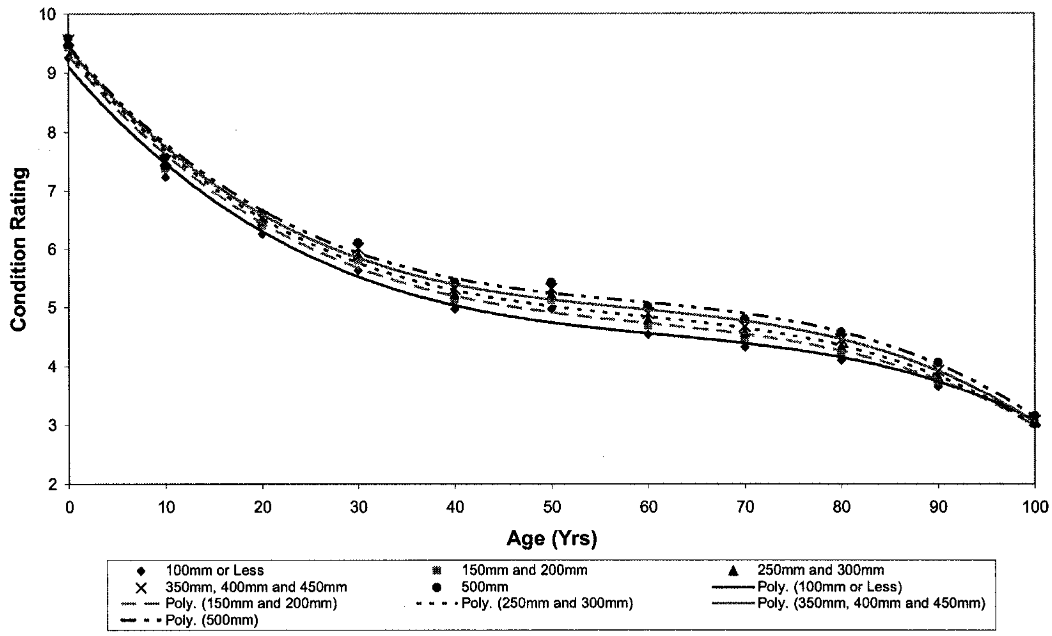


Figure E-9 DI: C-factor (100) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

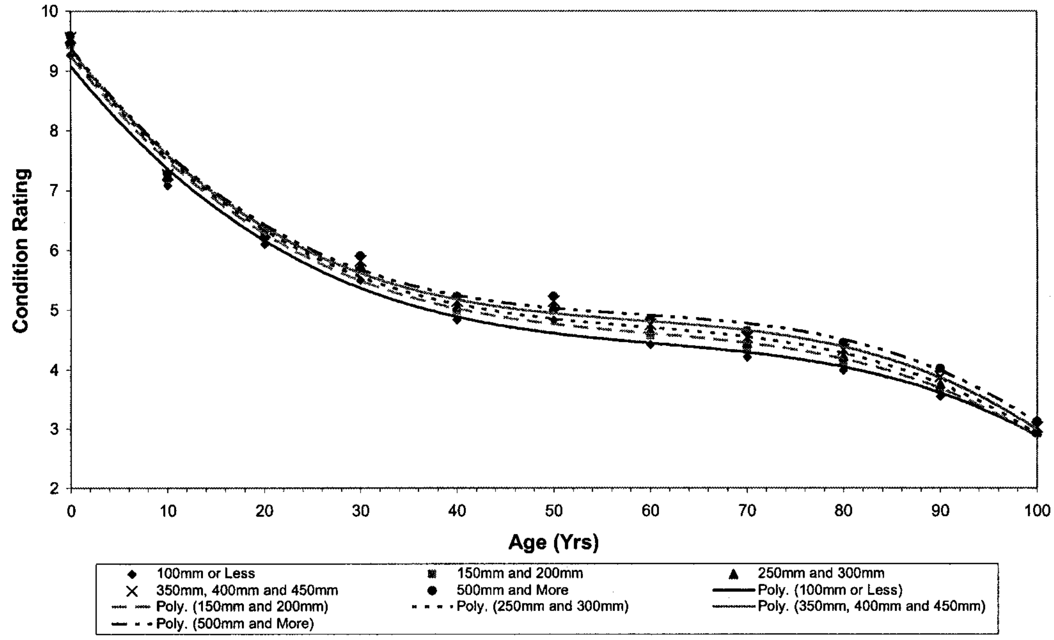


Figure E-10 DI: C-factor (80) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

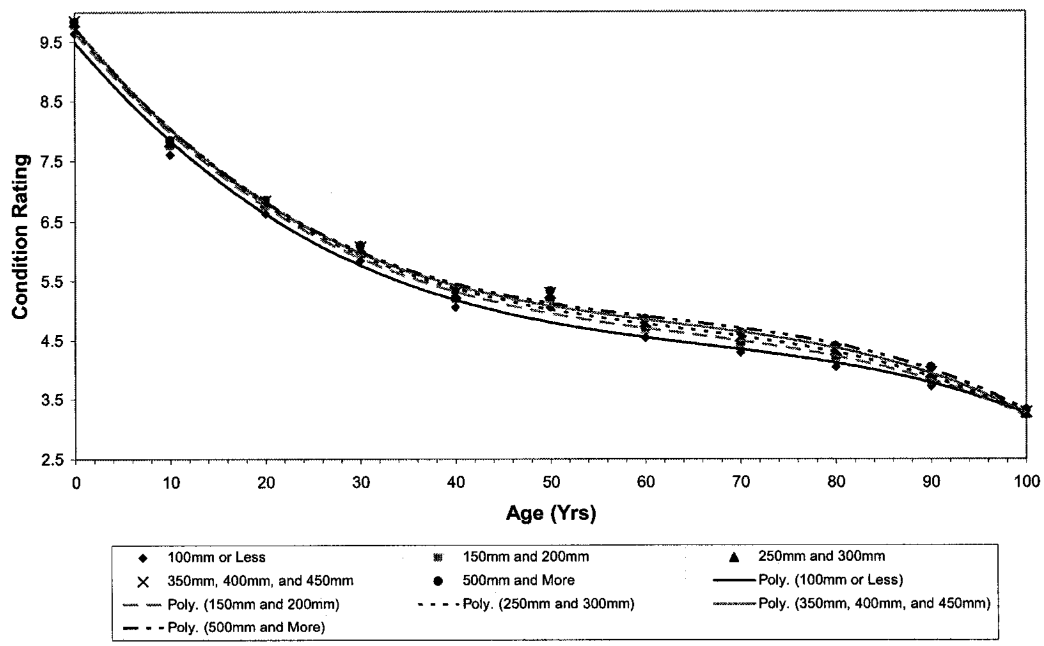


Figure E-11 DI: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

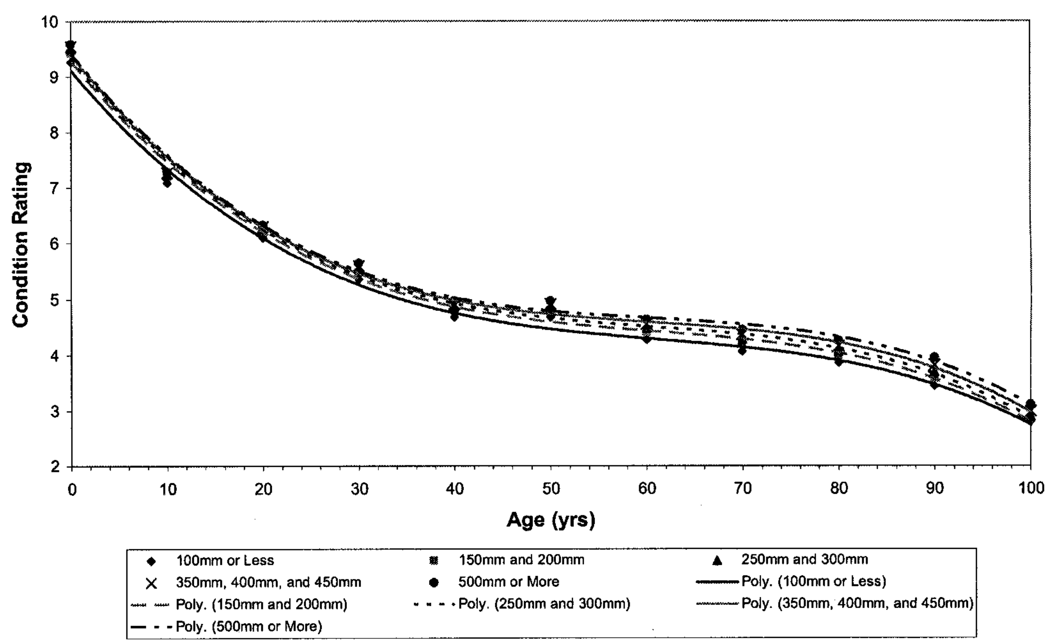


Figure E-12 DI: C-factor (60) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

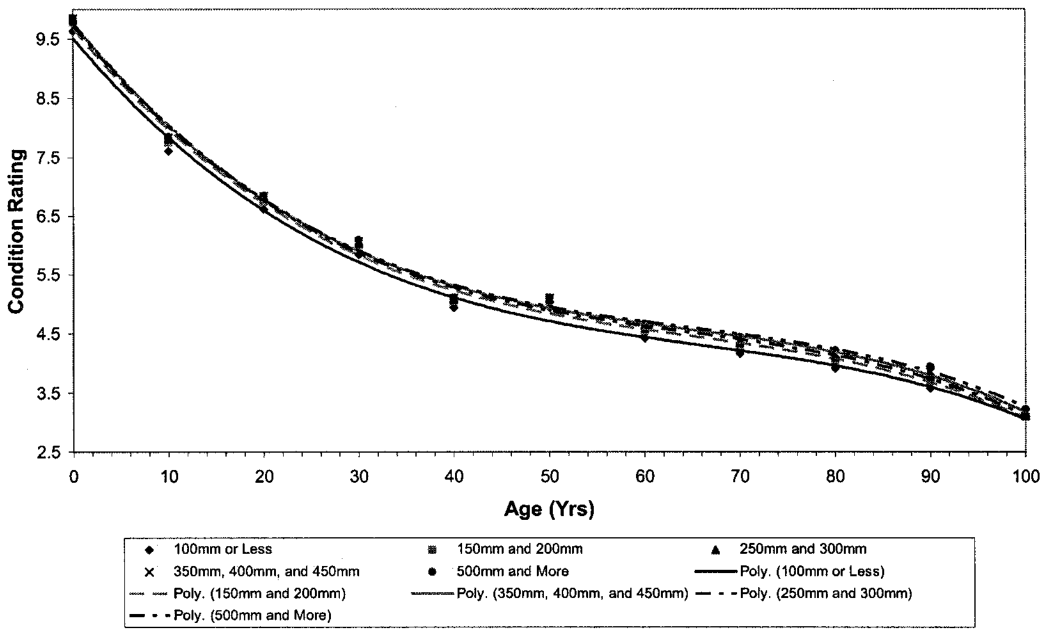


Figure E-13 DI: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

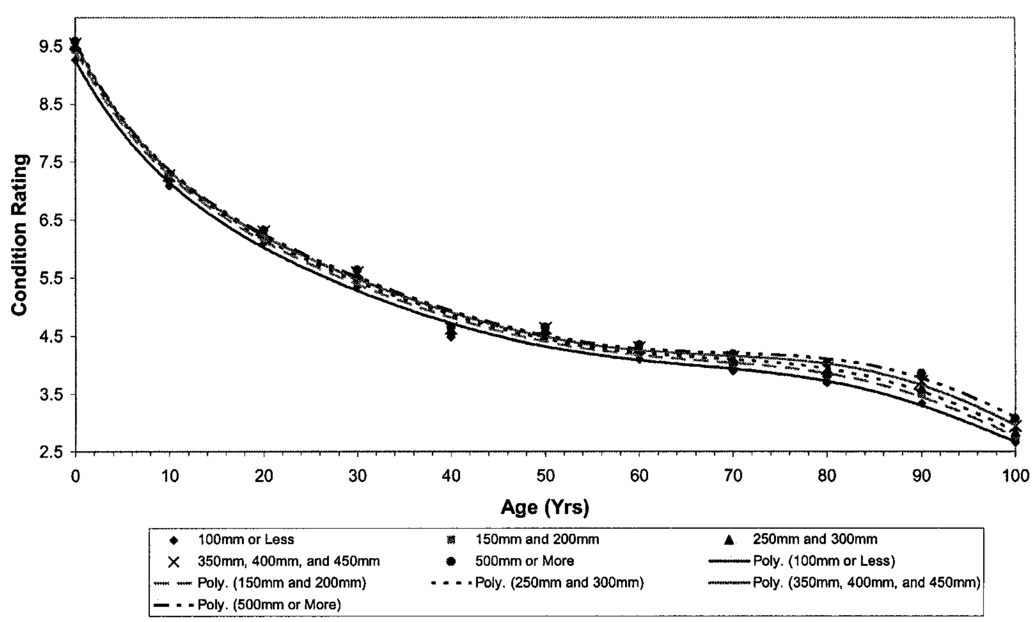


Figure E-14 DI: C-factor (40) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

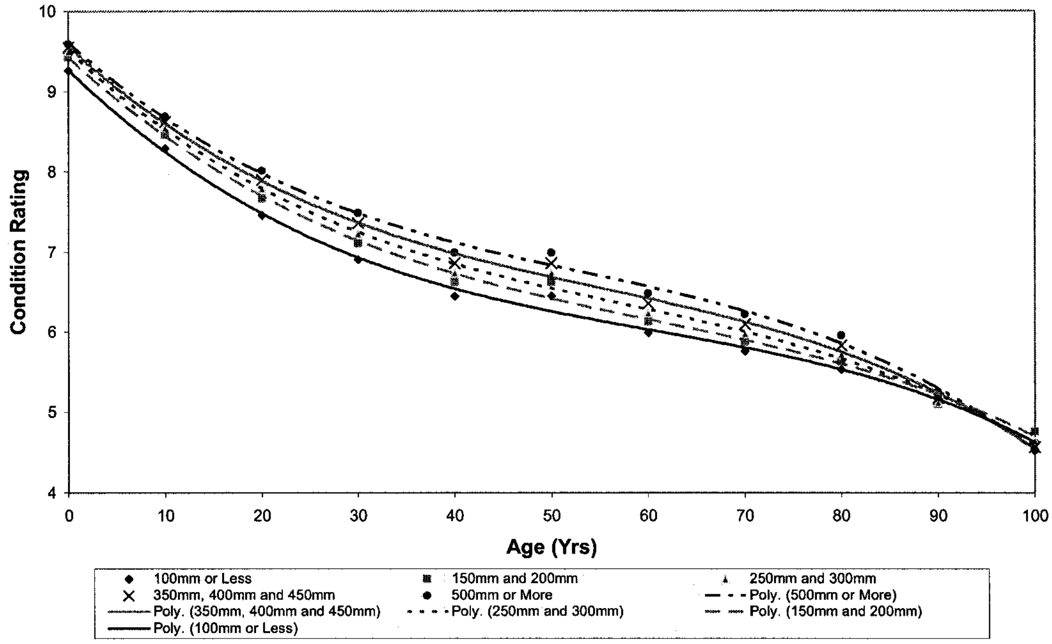


Figure E-15 DI: C-factor (120)- Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

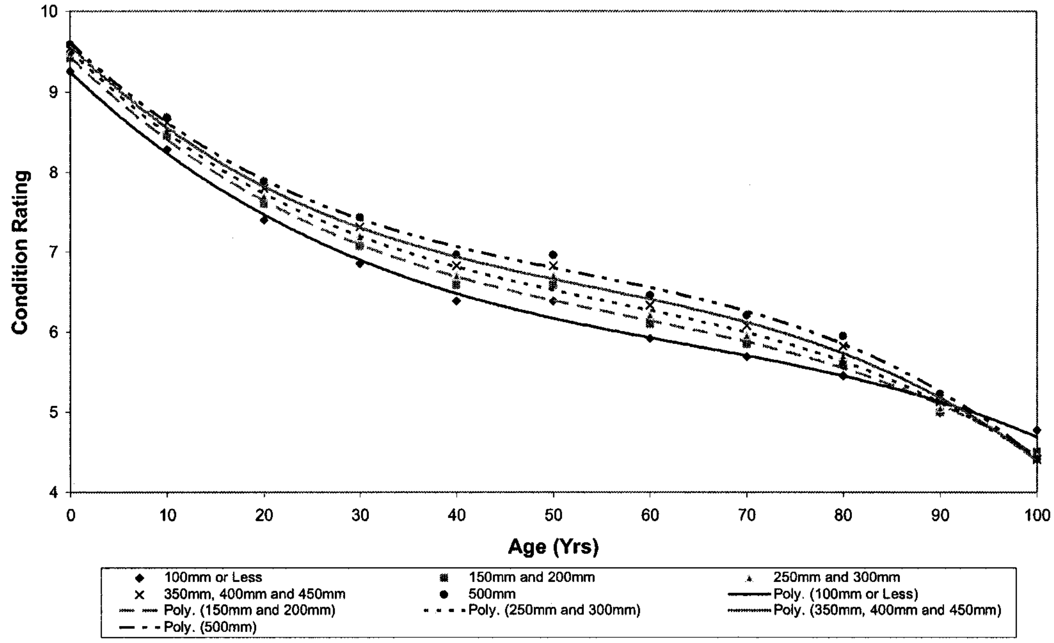


Figure E-16 DI: C-factor (100)- Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

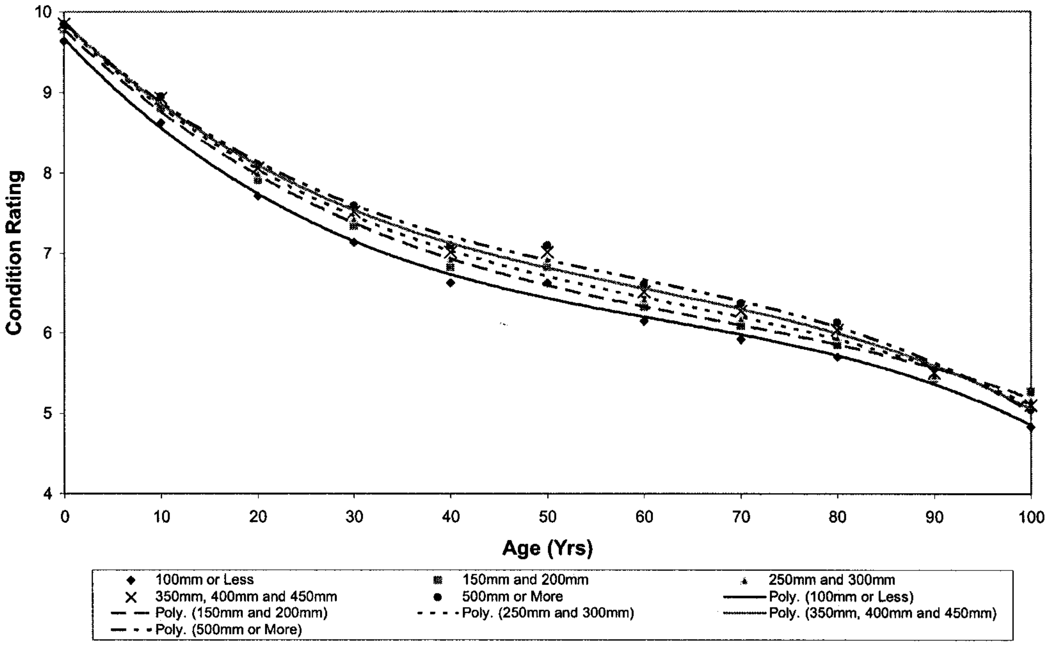


Figure E-17 DI: C-factor (80)- Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

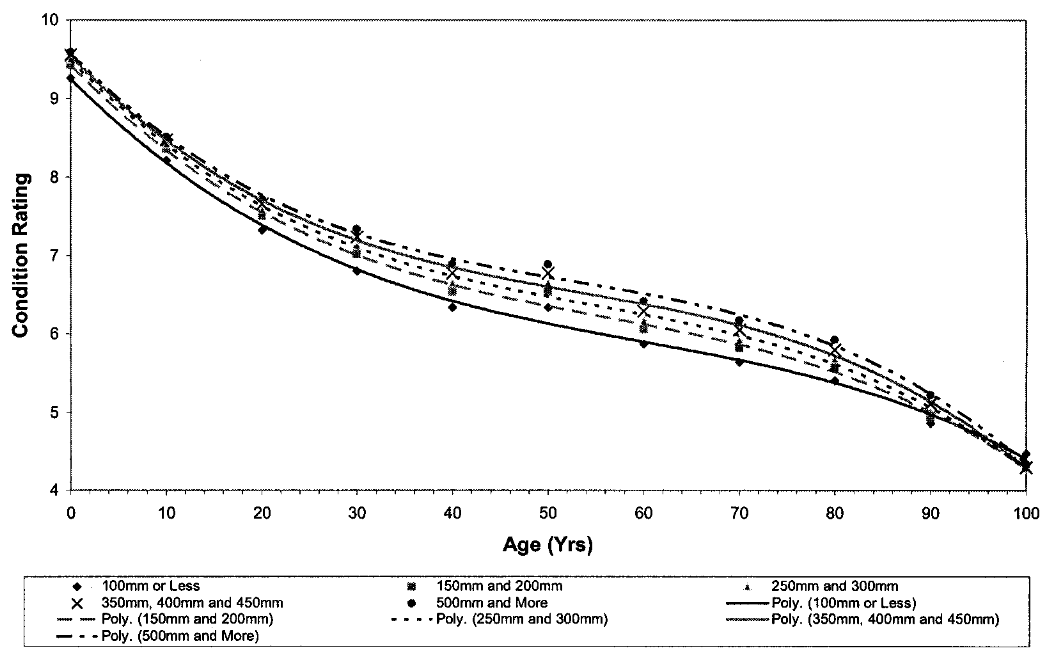


Figure E-18 DI: C-factor (80) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

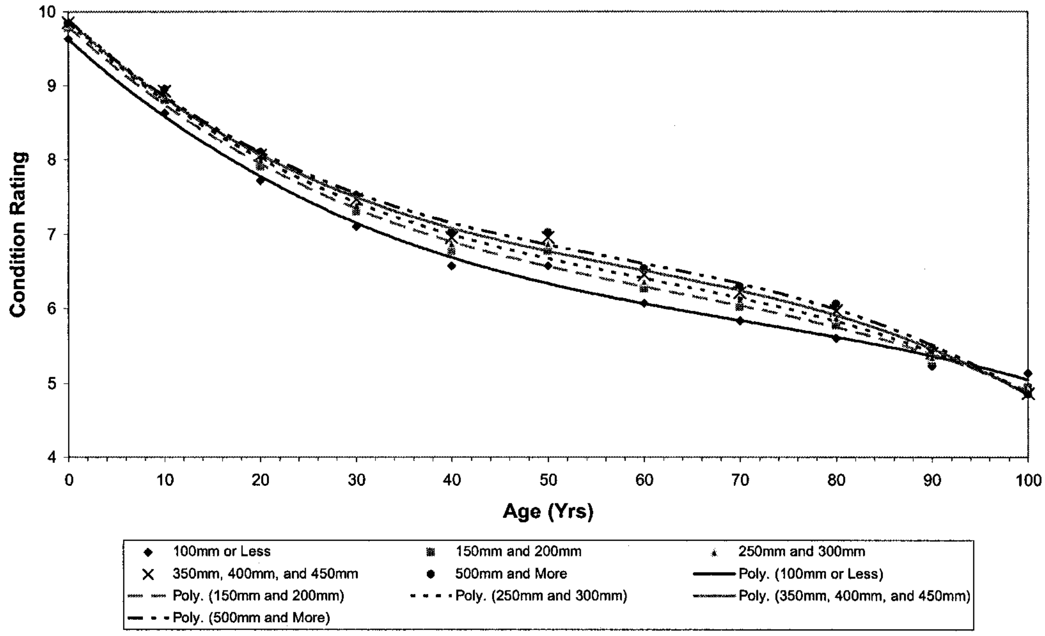


Figure E-19 DI: C-factor (60)- Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

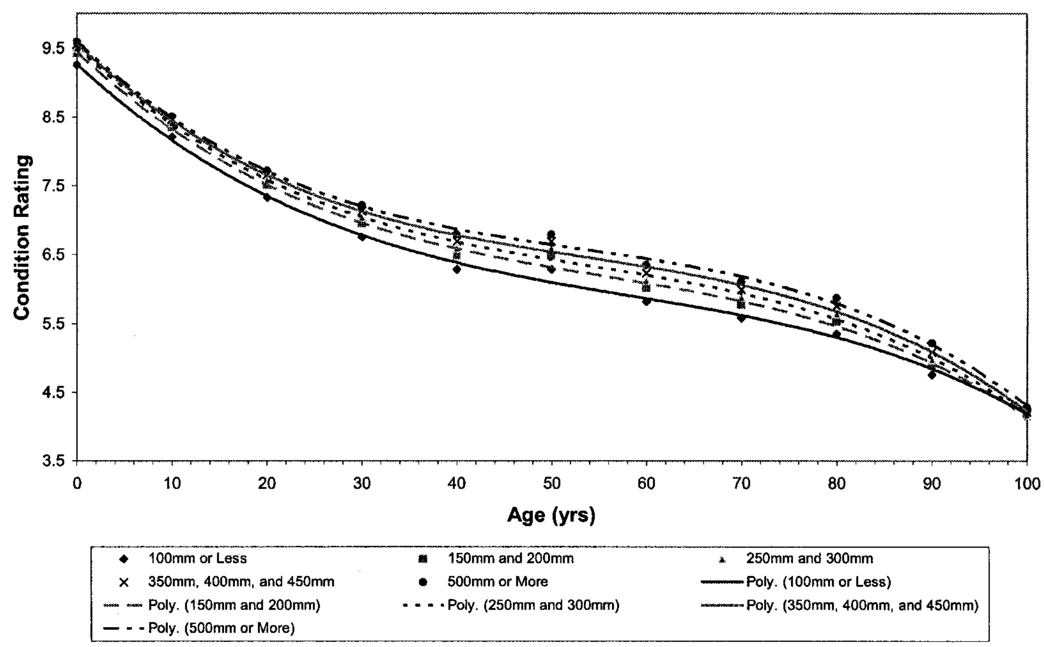


Figure E-20 DI: C-factor (60) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

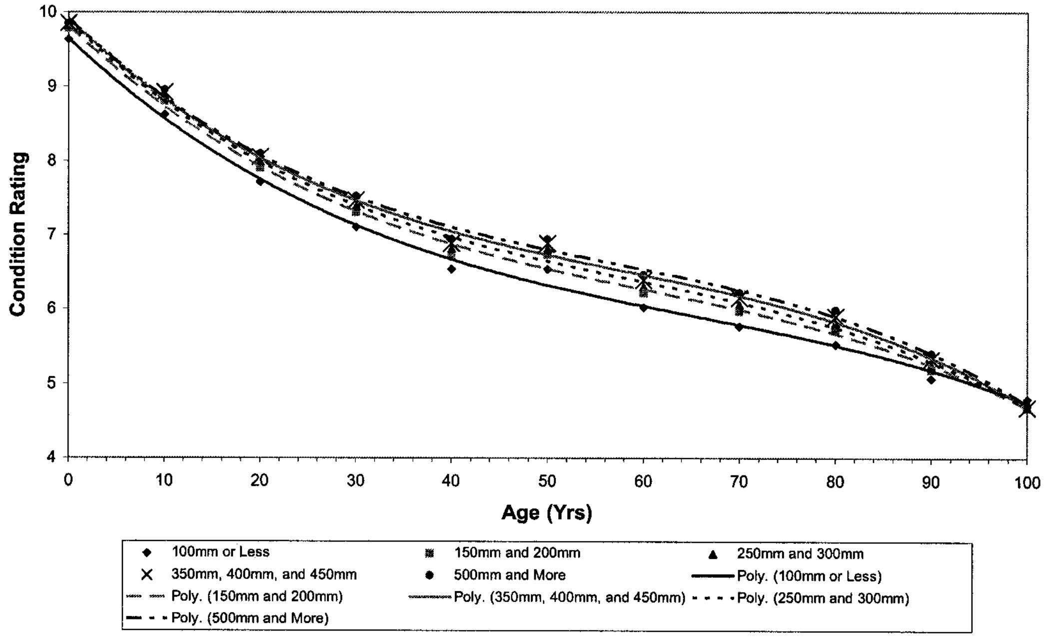


Figure E-21 DI: C-factor (40)- Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

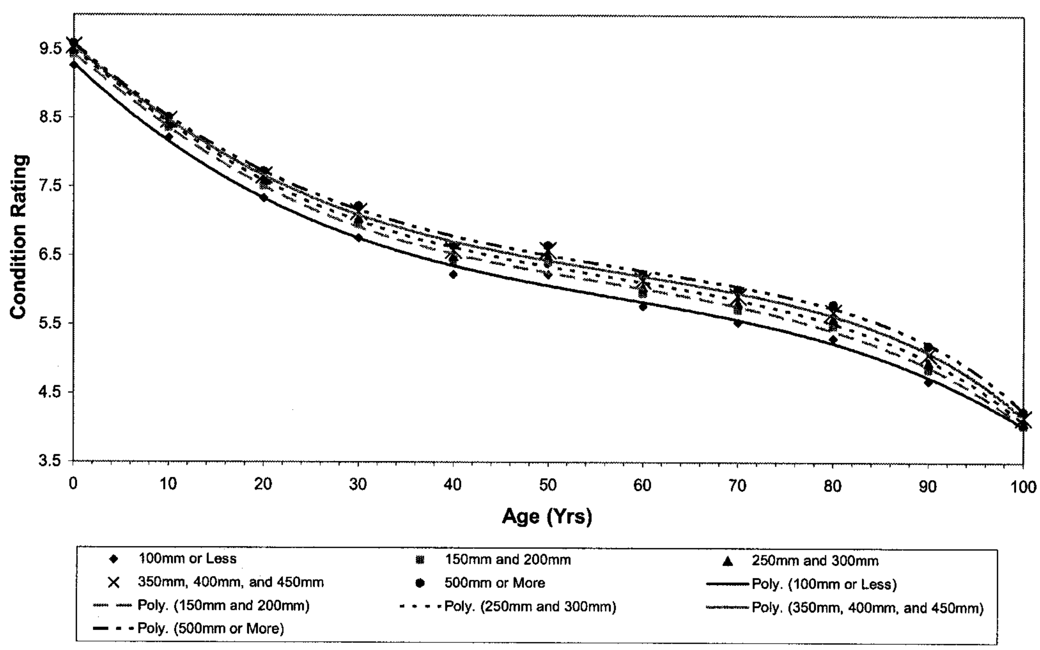


Figure E-22 DI: C-factor (40) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

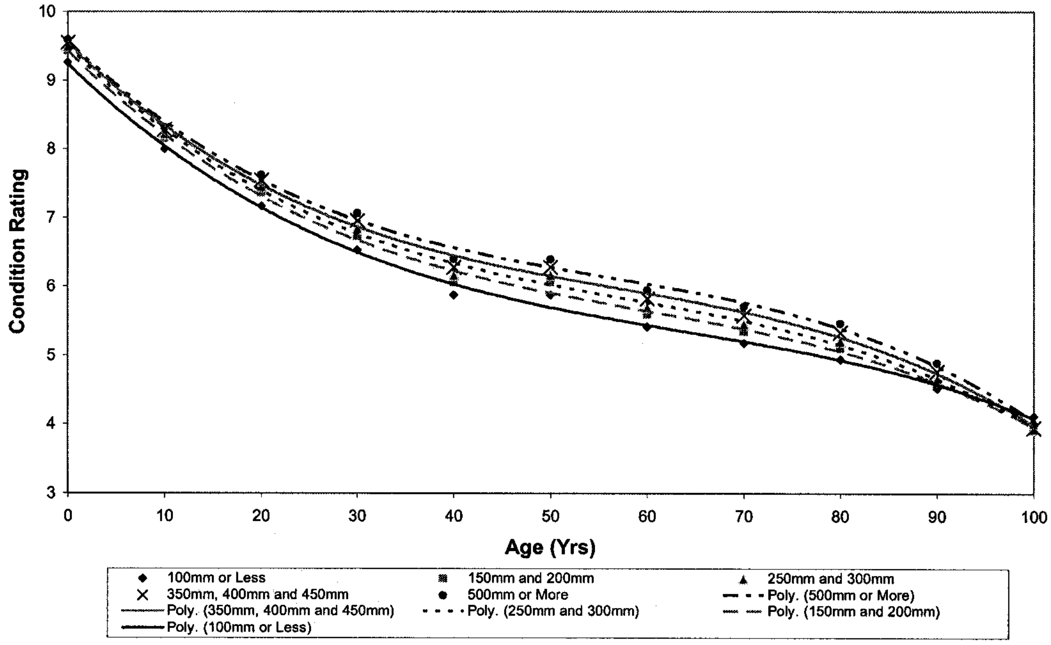


Figure E-23 DI: C-factor (120)-Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

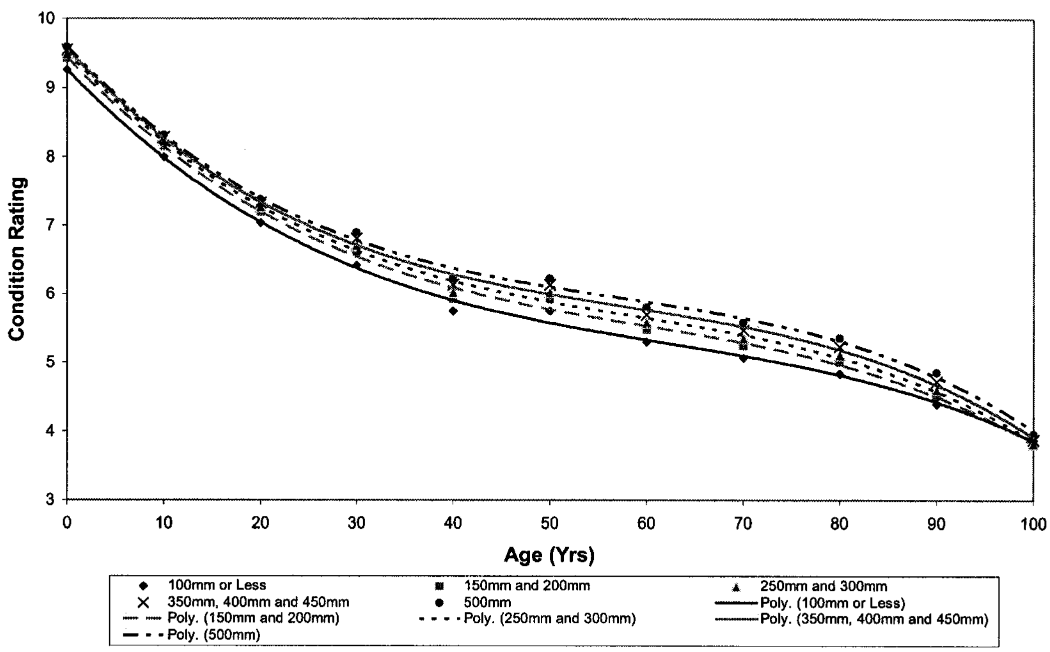


Figure E-24 DI: C-factor (100)-Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

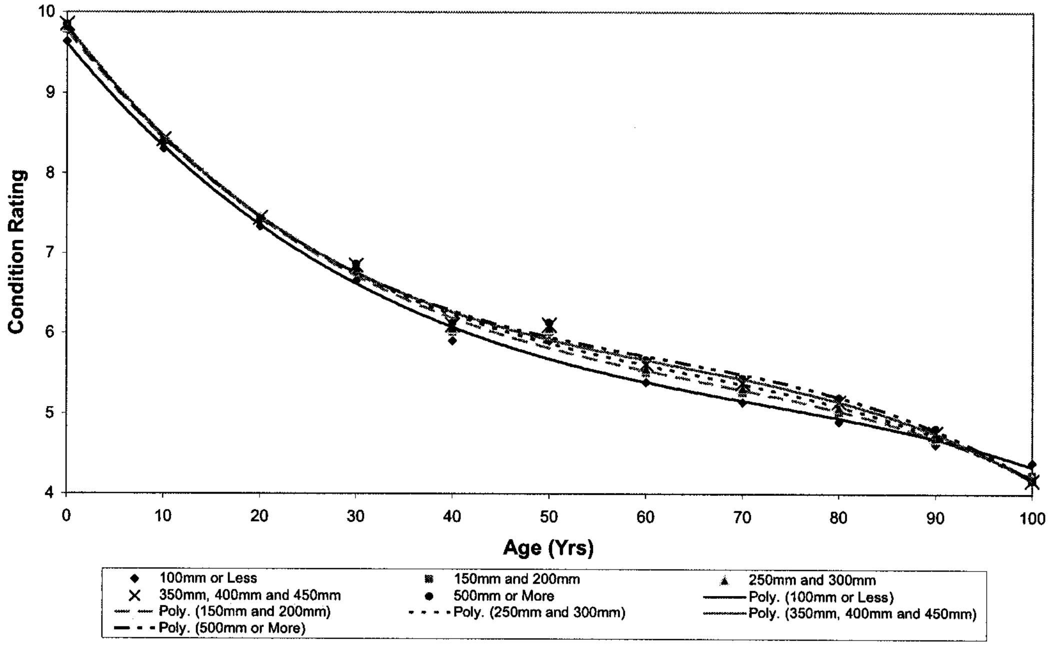


Figure E-25 DI: C-factor (80)-Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

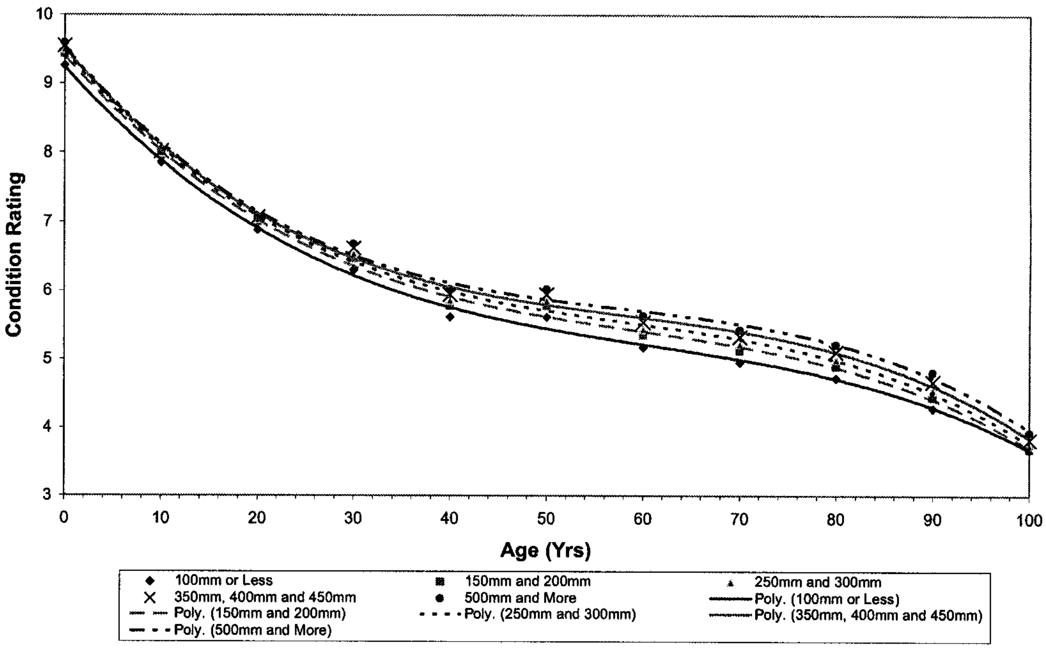


Figure E-26 DI: C-factor (80)-Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

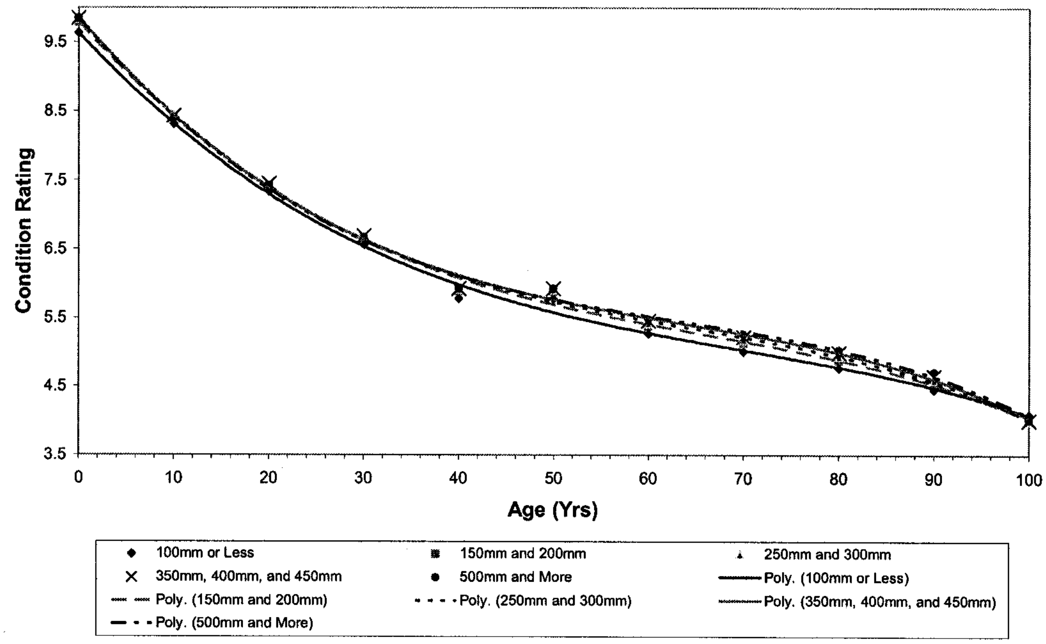


Figure E-27 DI: C-factor (60)-Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

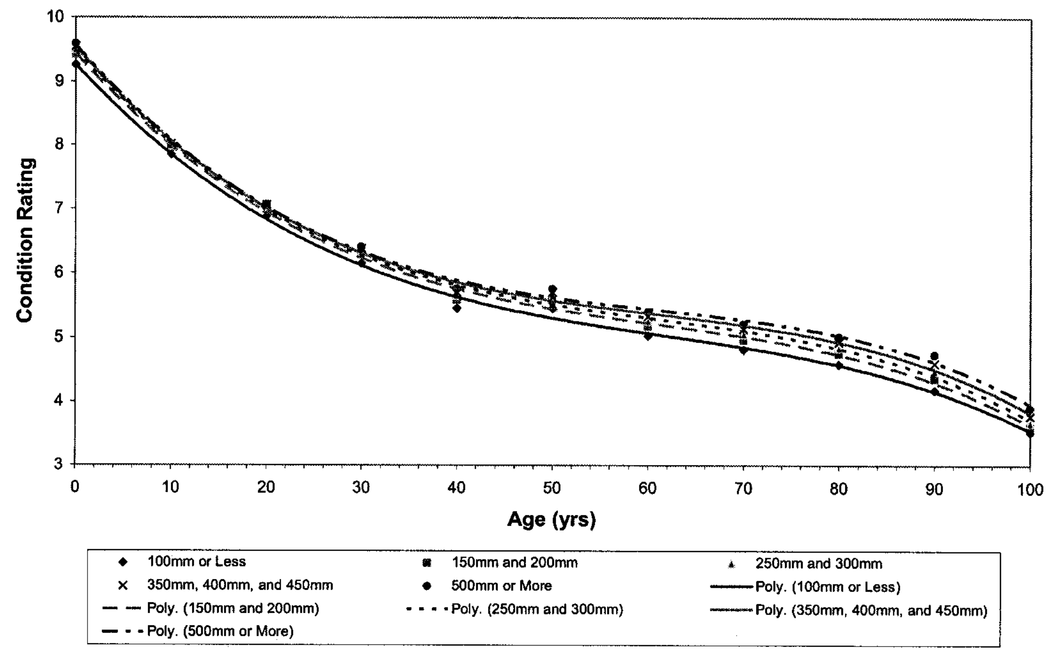


Figure E-28 DI: C-factor (60)-Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

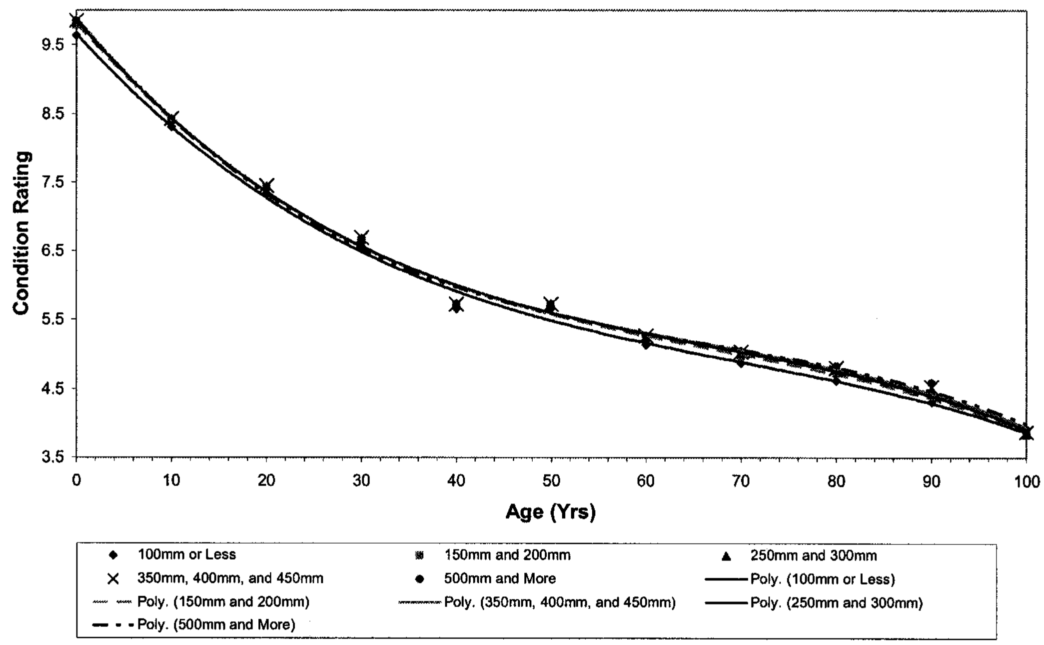


Figure E-29 DI: C-factor (40)-Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

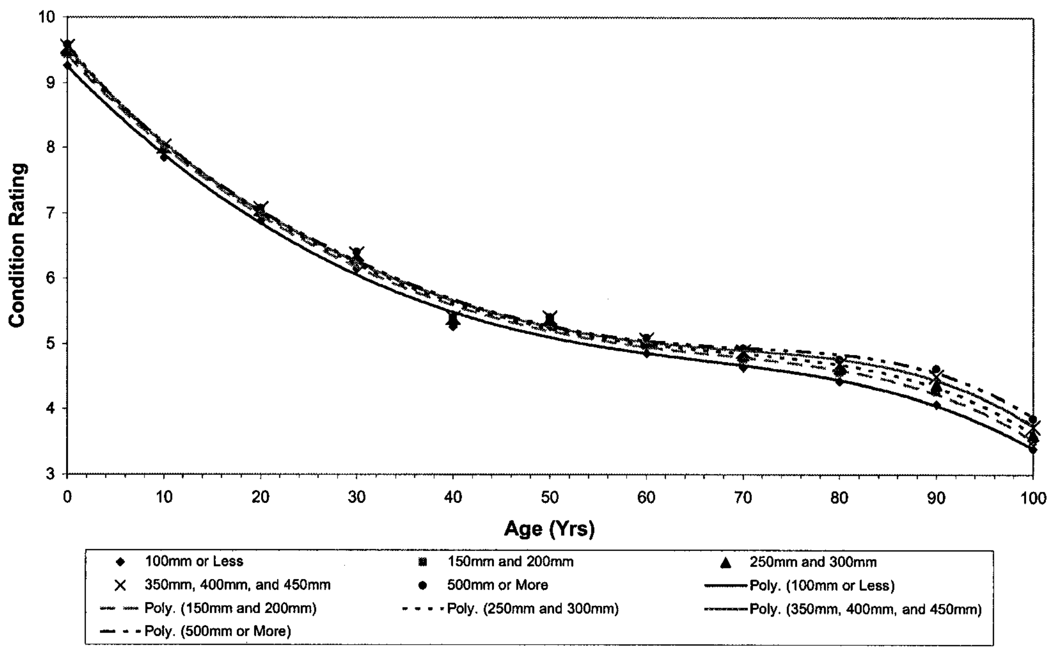


Figure E-30 DI: C-factor (40)-Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

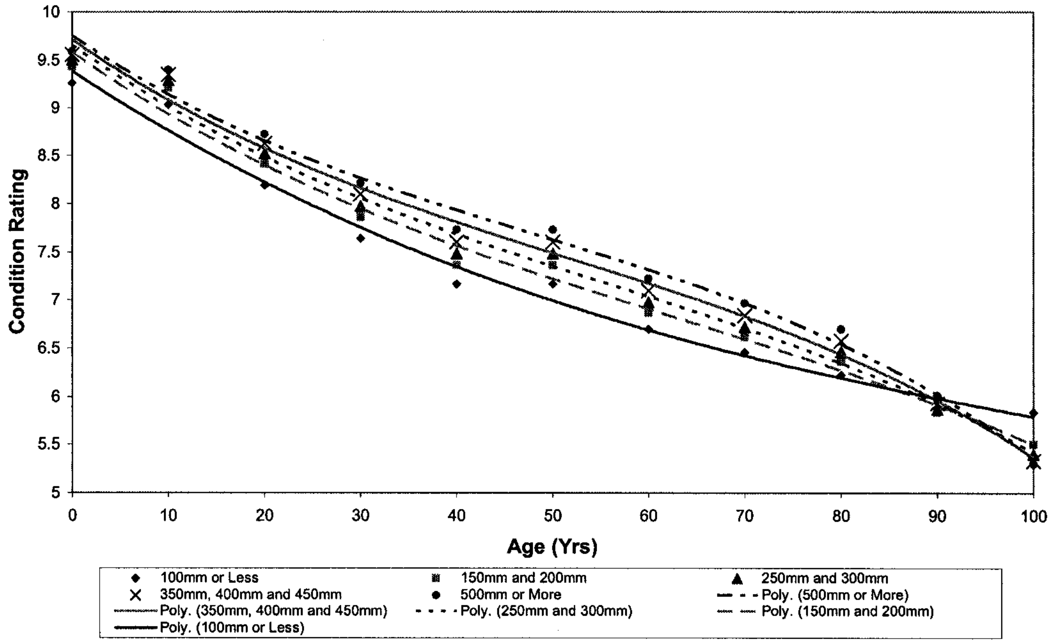


Figure E-31 DI: C-factor (120)- Cathodic Protection (No)- Soil Type (Sand) - Breakage Rate (0.1)

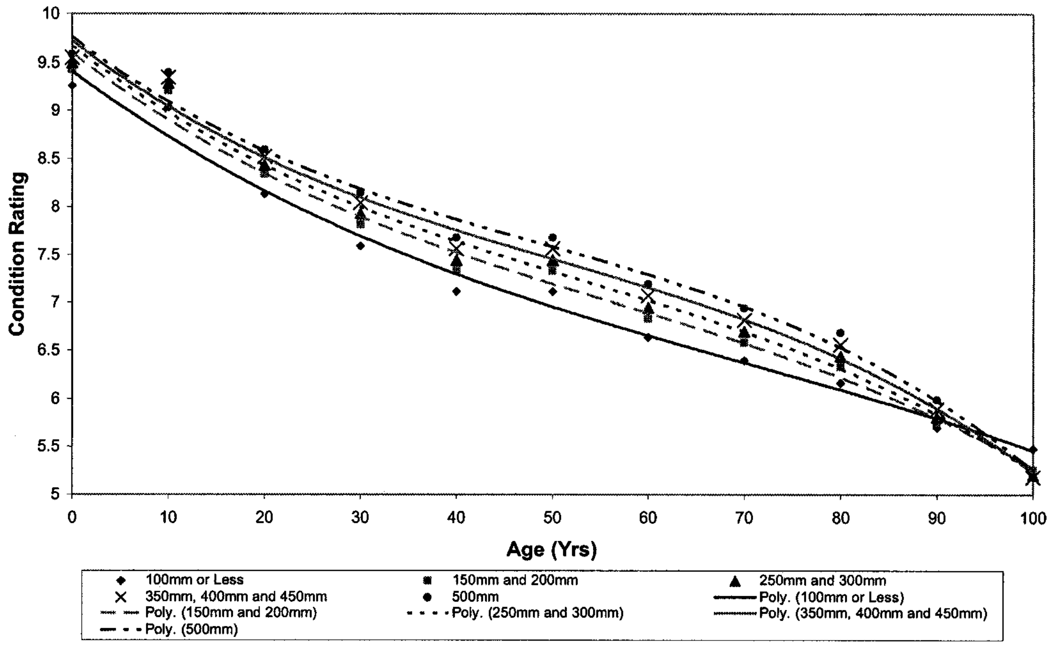


Figure E-32 DI: C-factor (100)- Cathodic Protection (No)- Soil Type (Sand) - Breakage Rate (0.1)

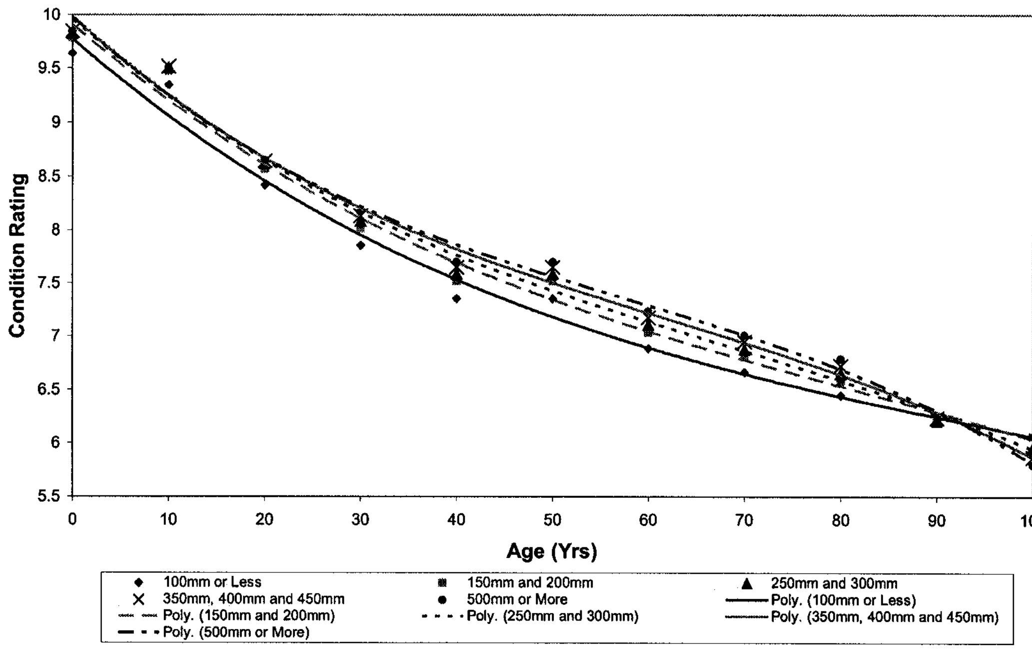


Figure E-33 DI: C-factor (80)- Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

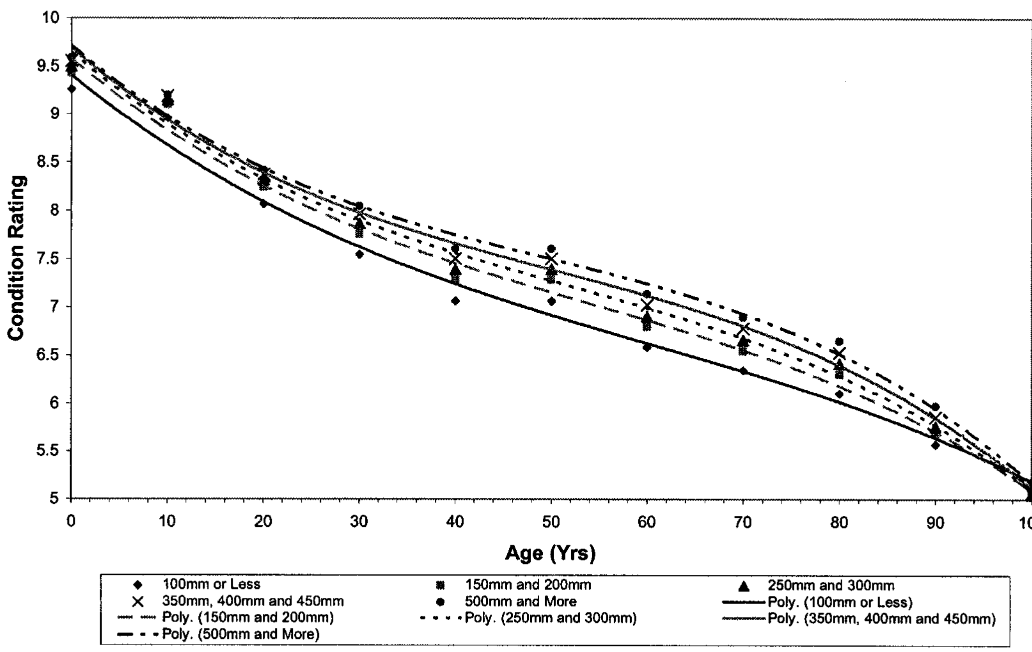


Figure E-34 DI: C-factor (80) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

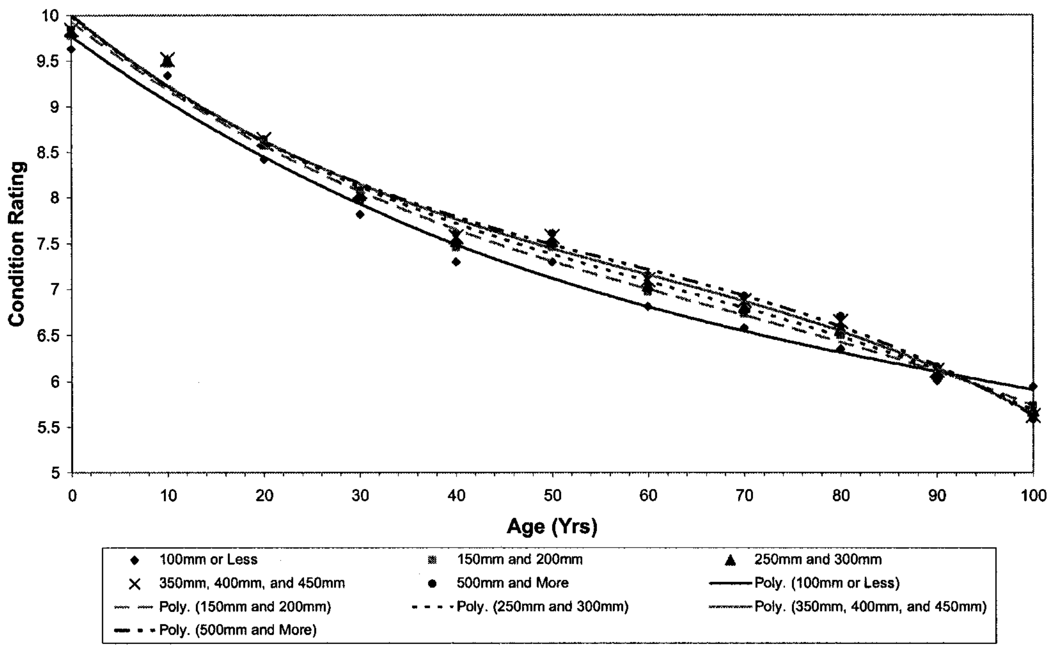


Figure E-35 DI: C-factor (60)- Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

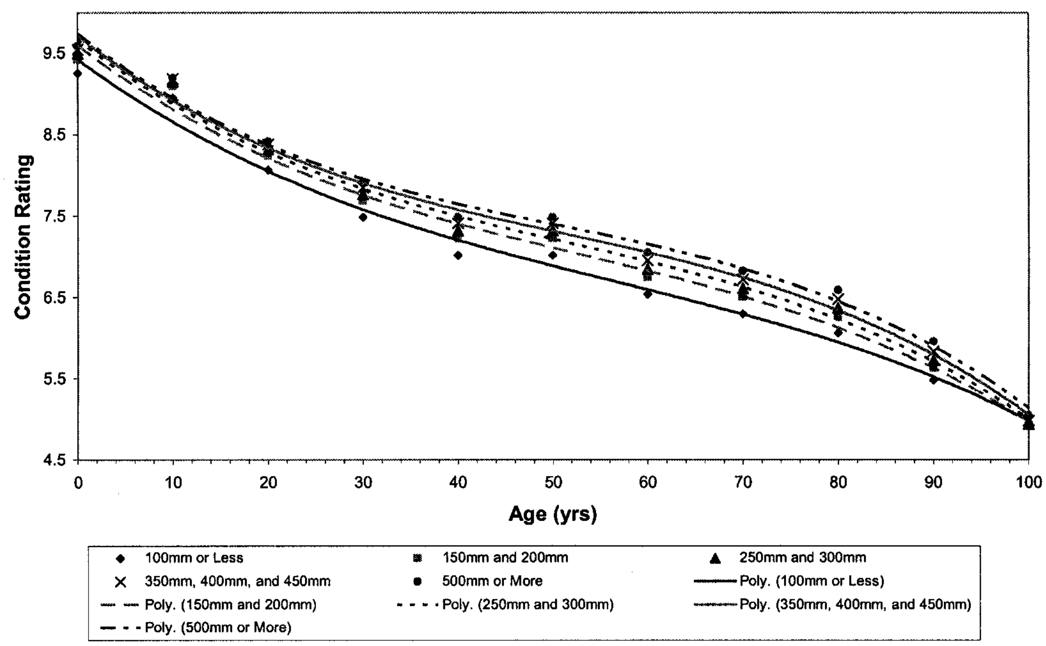


Figure E-36 DI: C-factor (60) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

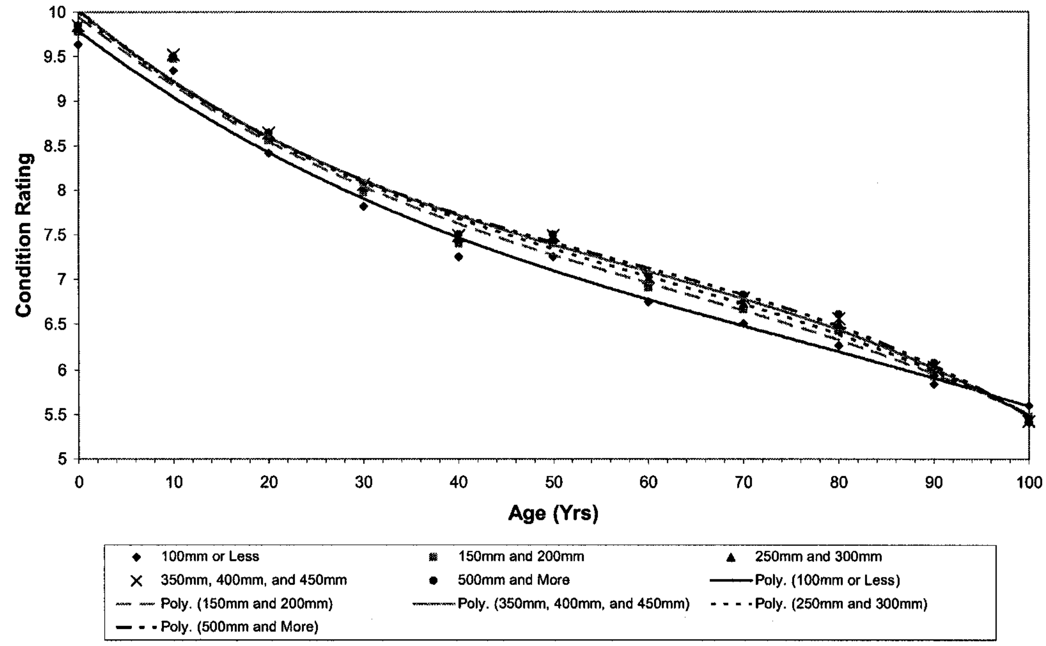


Figure E-37 DI: C-factor (40)- Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

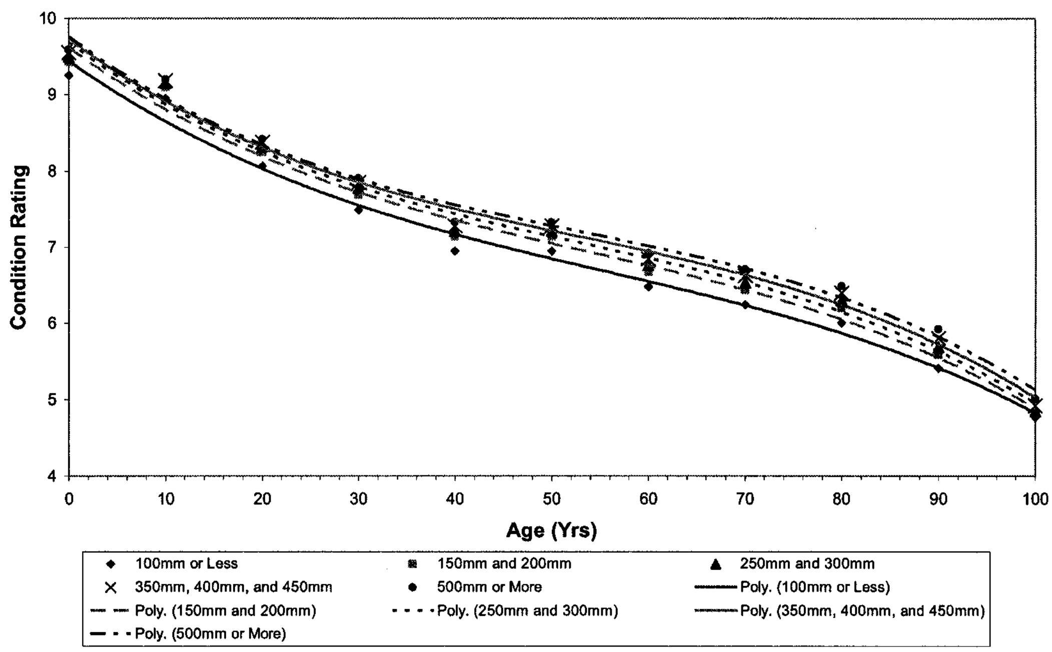


Figure E-38 DI: C-factor (40) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

E.2. CAST IRON PREDICTION CURVES (After WW II)

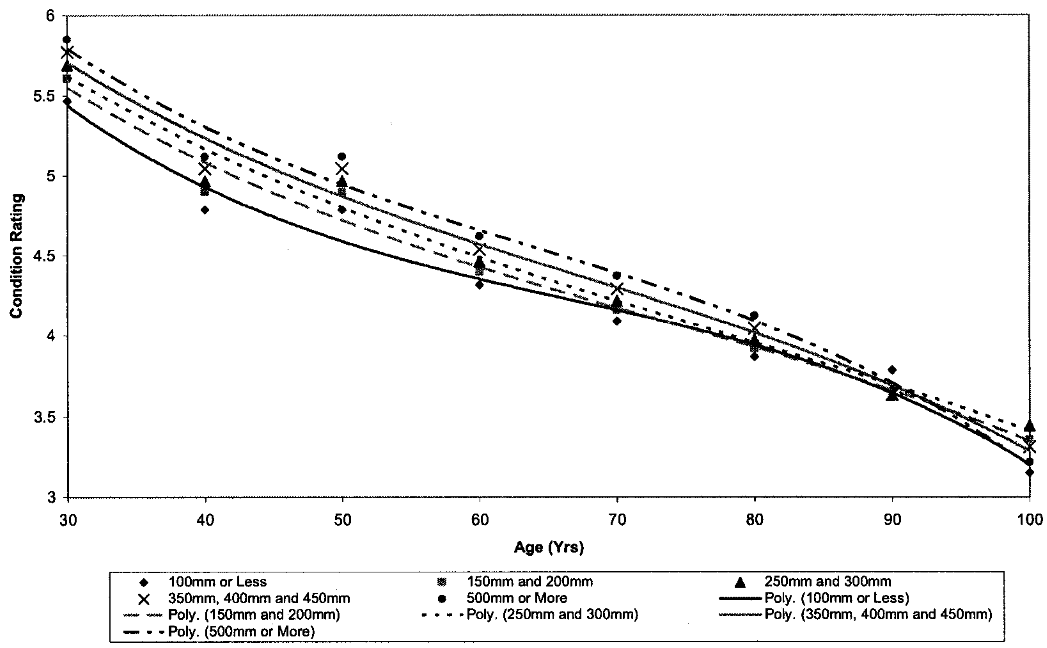


Figure E-39 CI-A: C-factor (80)- Cathodic Protection (Yes) - Soil Type (Clay)- Breakage Rate (3)

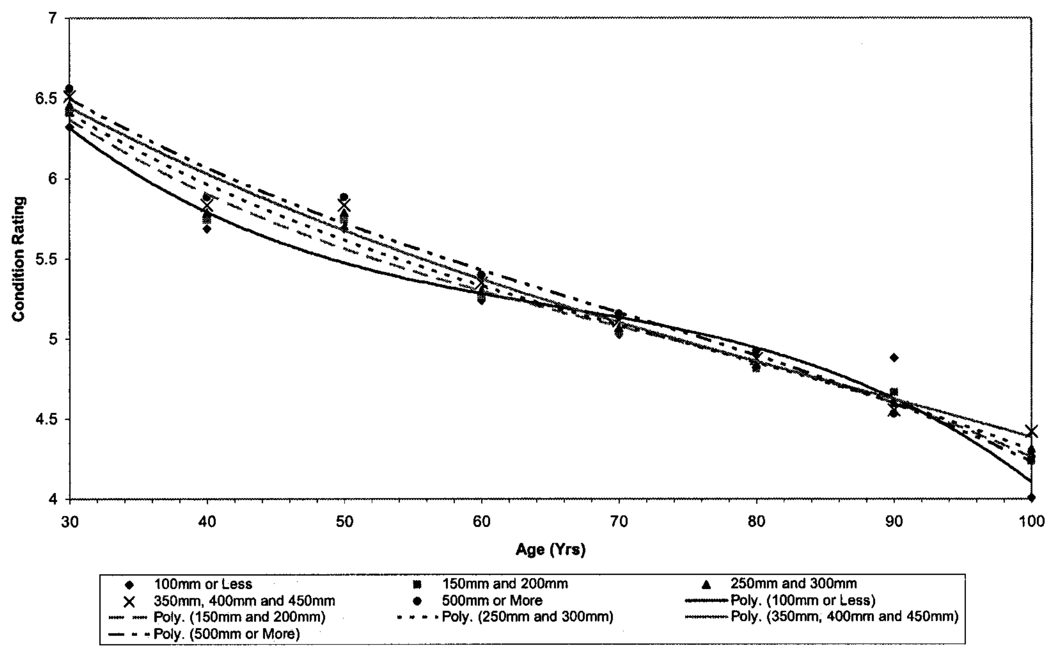


Figure E-40 CI-A: C-factor (100) - Cathodic Protection (Yes)- Soil Type (Sand)- Breakage Rate (3)

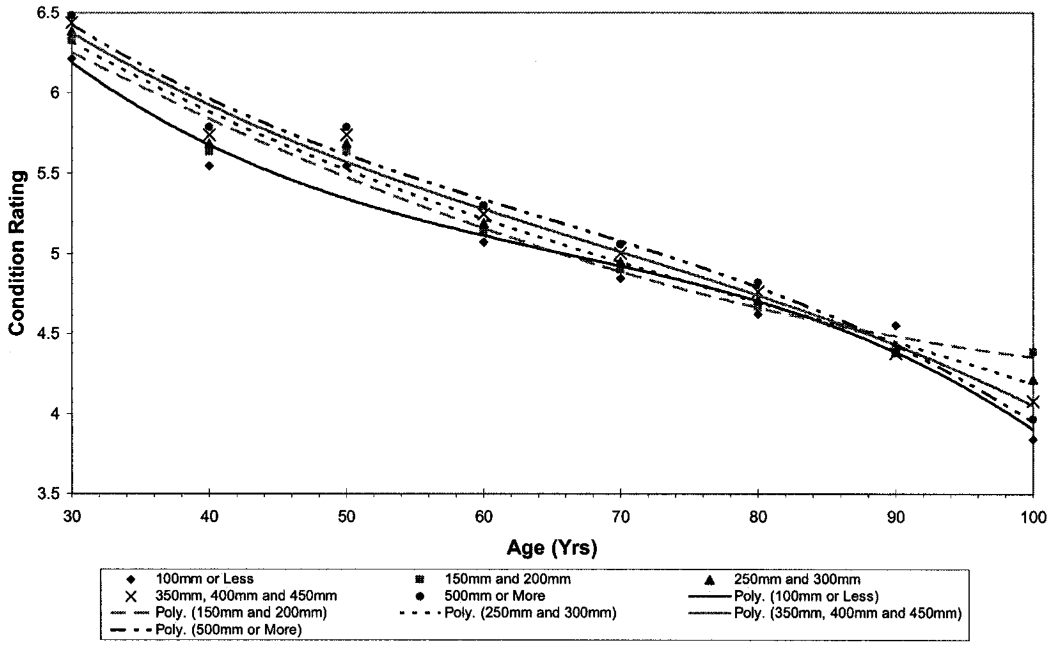


Figure E-41 CI-A: C-factor (80)- Cathodic Protection (Yes)- Soil Type (Sand)- Breakage Rate (3)

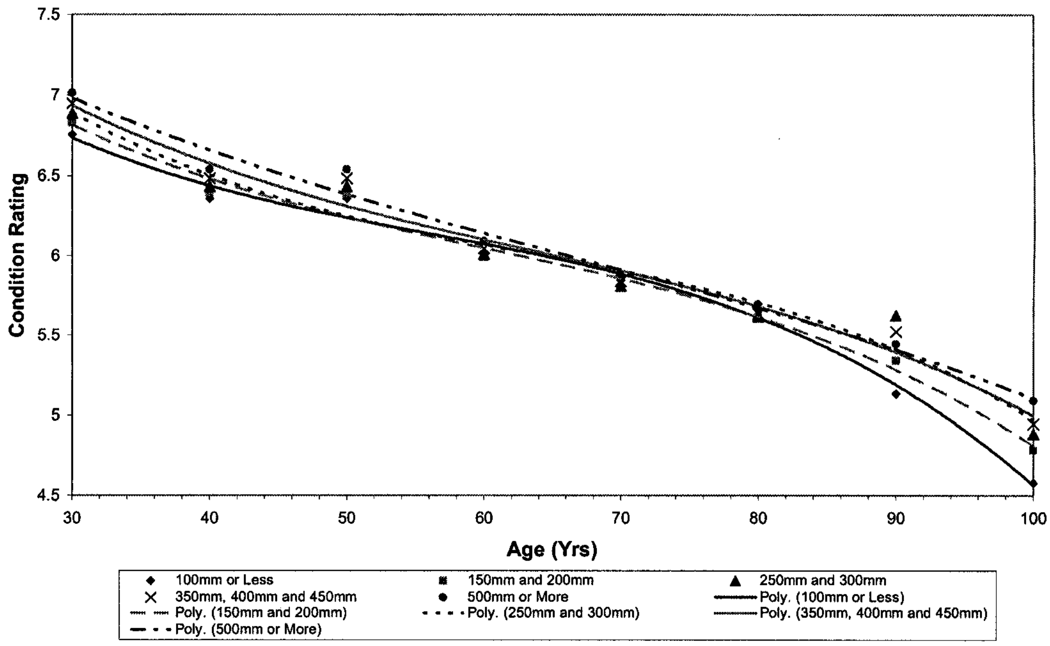


Figure E-42 CI-A: C-factor (100)- Cathodic Protection (Yes)- Soil Type (Clay)- Breakage Rate(0.1)

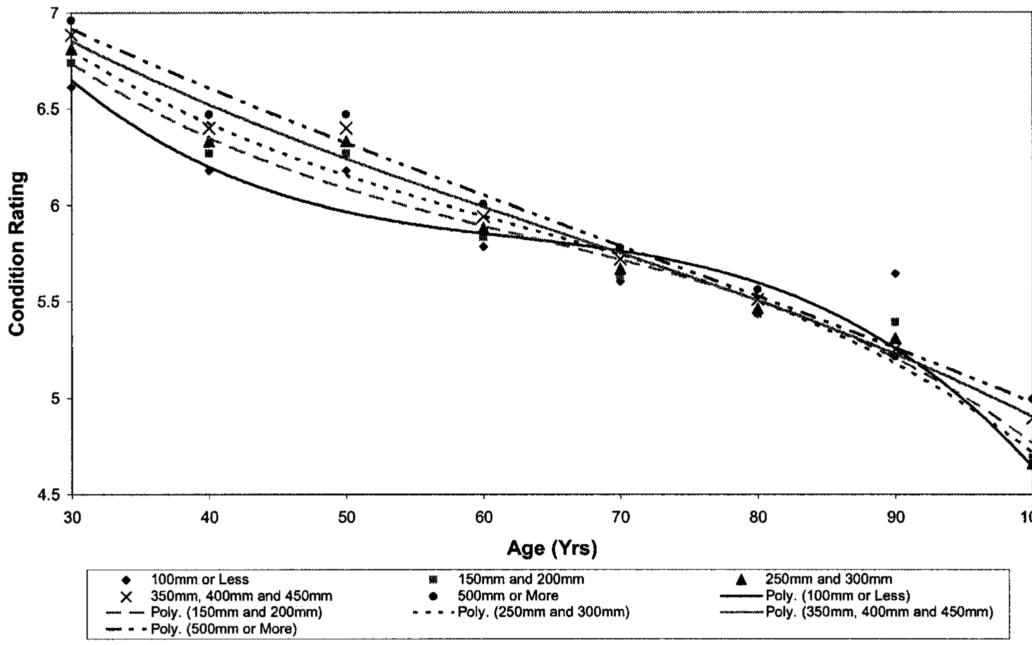


Figure E-43 CI-A: C-factor (80)- Cathodic Protection (Yes)- Soil Type (Clay)- Breakage Rate (0.1)

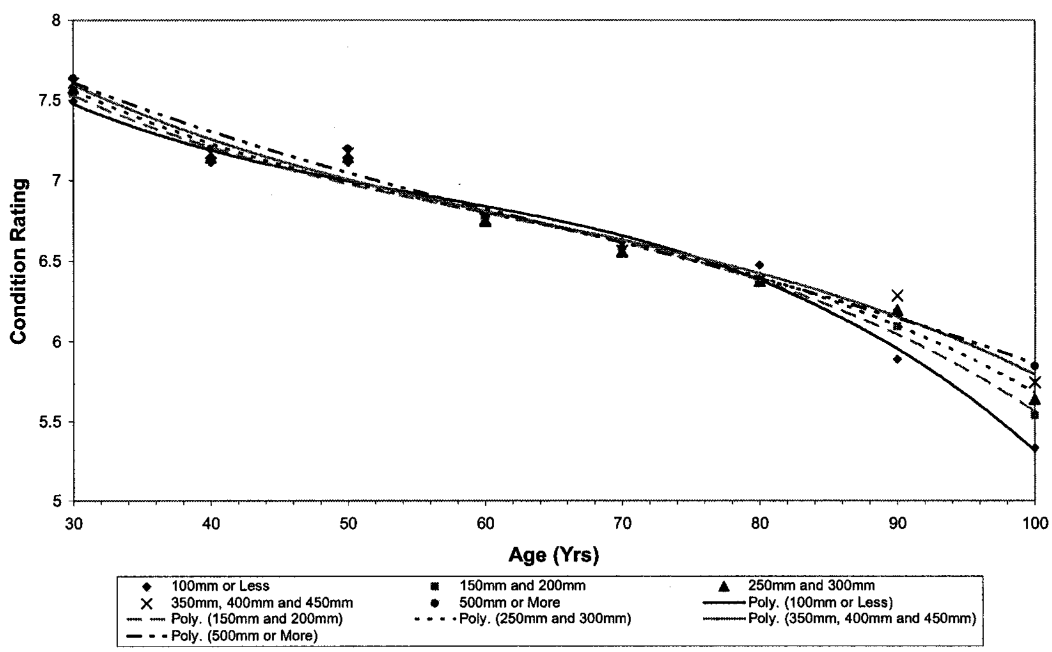


Figure E-44 CI-A: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Sand)- Breakage Rate (0.1)

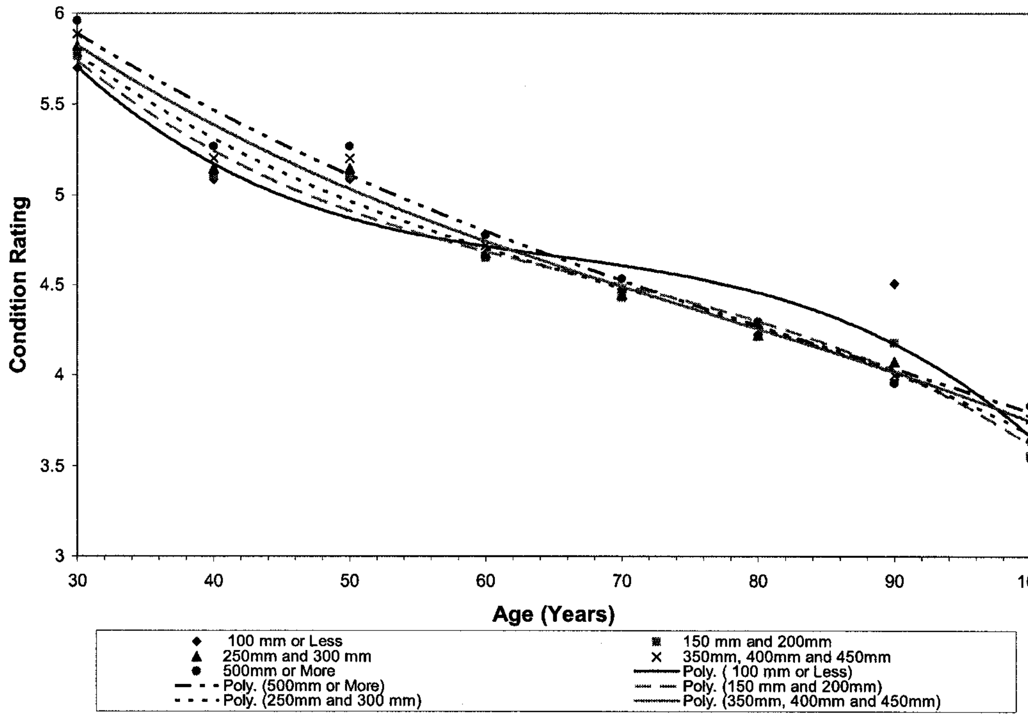


Figure E-45 CI-A: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

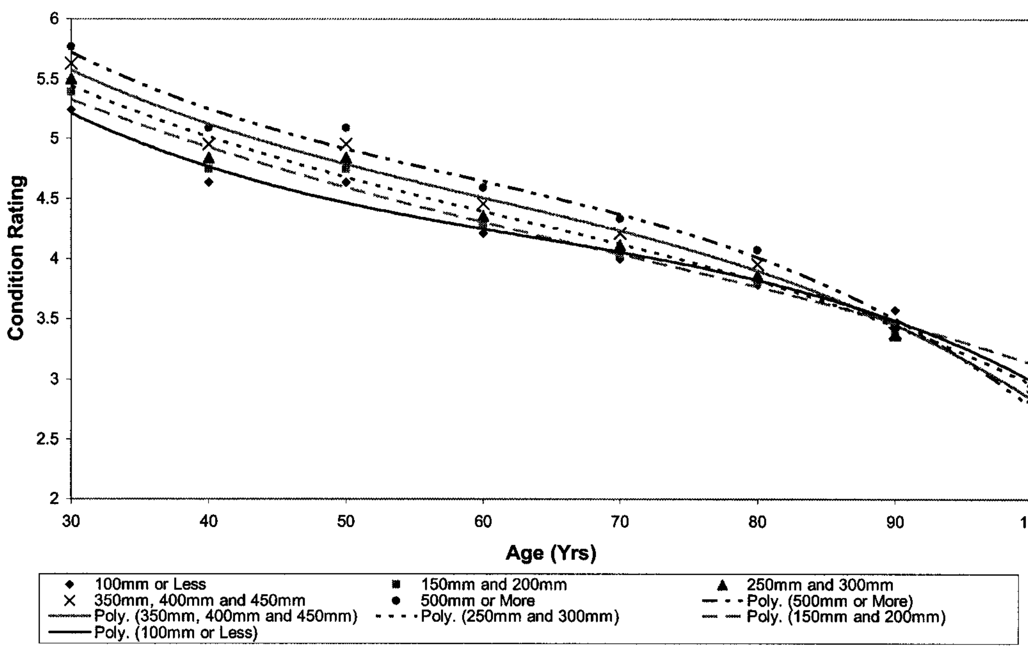


Figure E-46 CI-A: C-factor (120) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

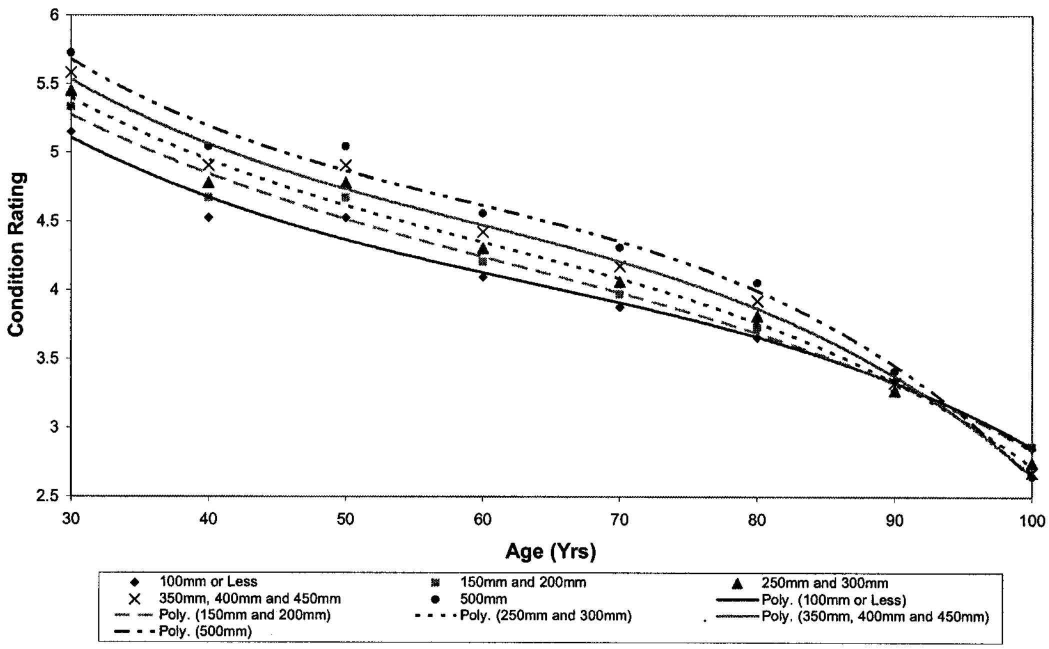


Figure E-47 CI-A: C-factor (100) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

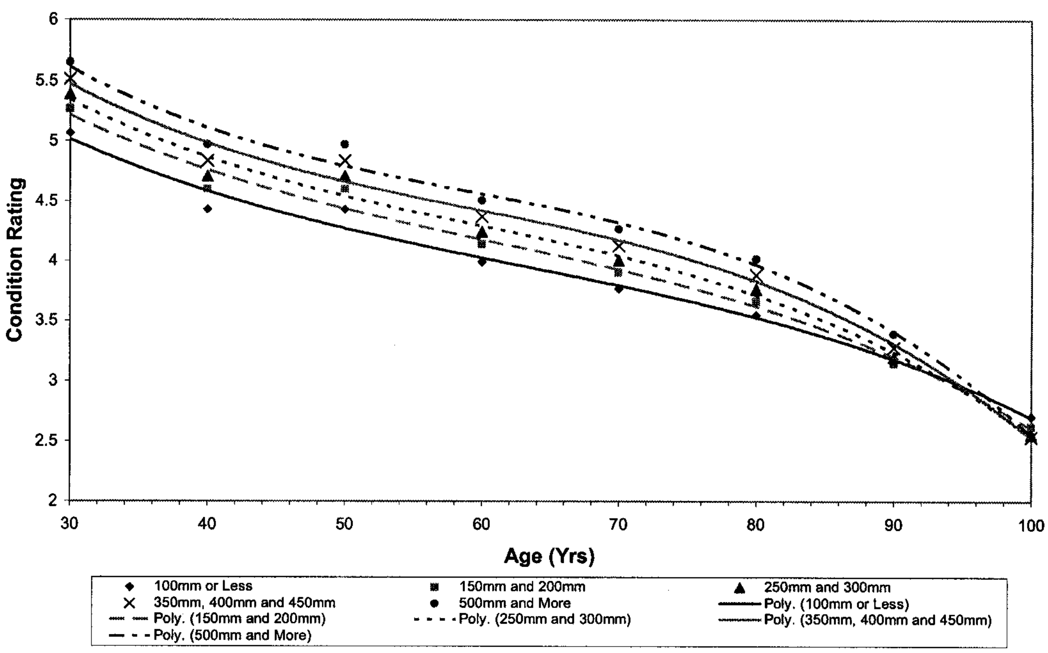


Figure E-48 CI-A: C-factor (80) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

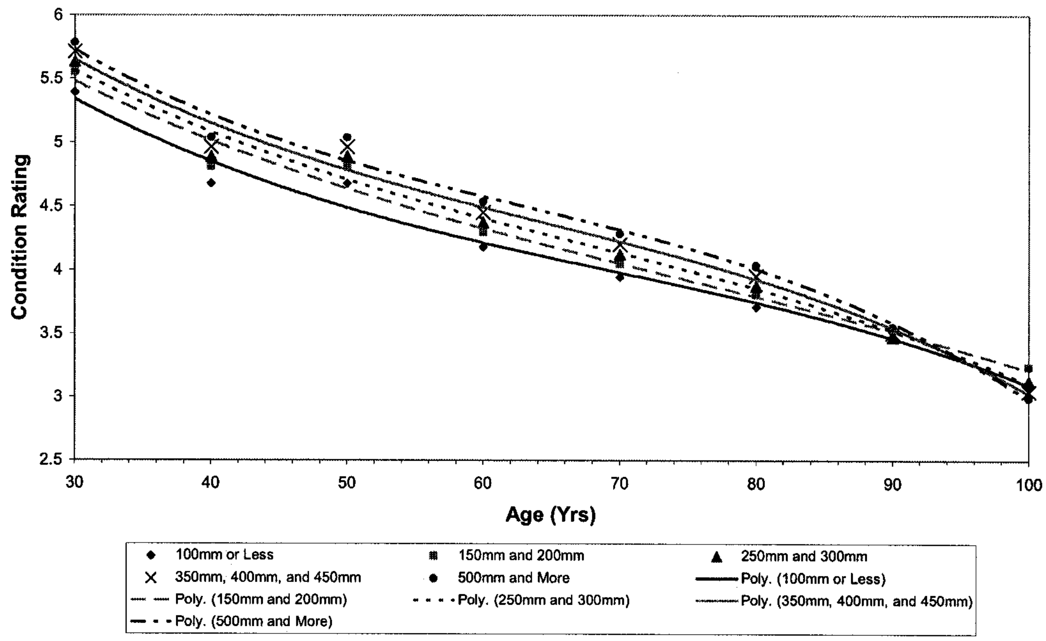


Figure E-49 CI-A: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

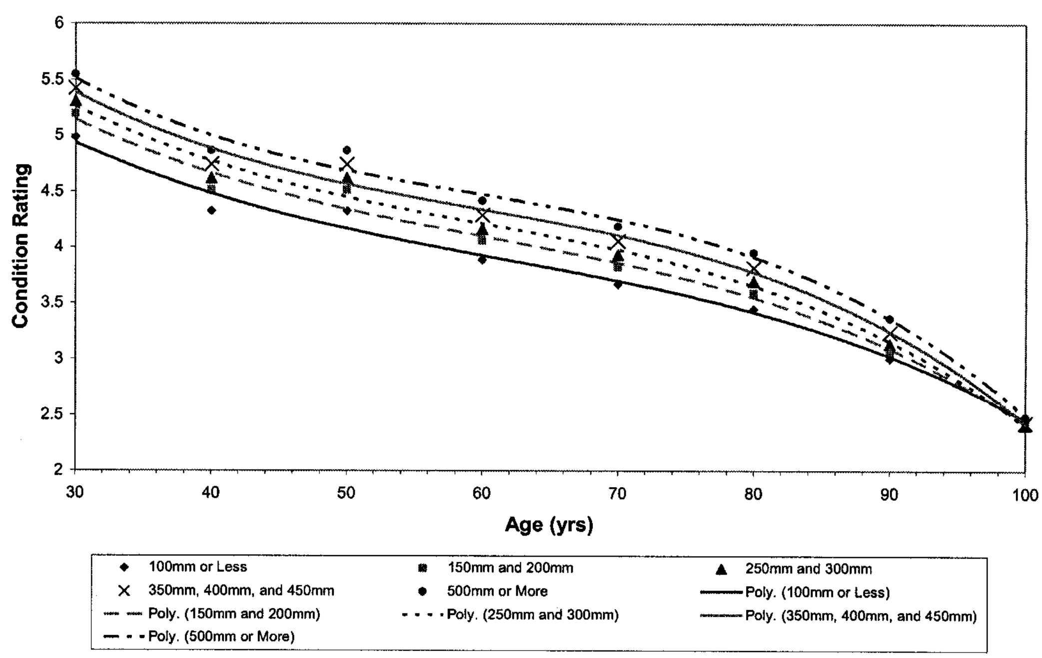


Figure E-50 CI-A: C-factor (60) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

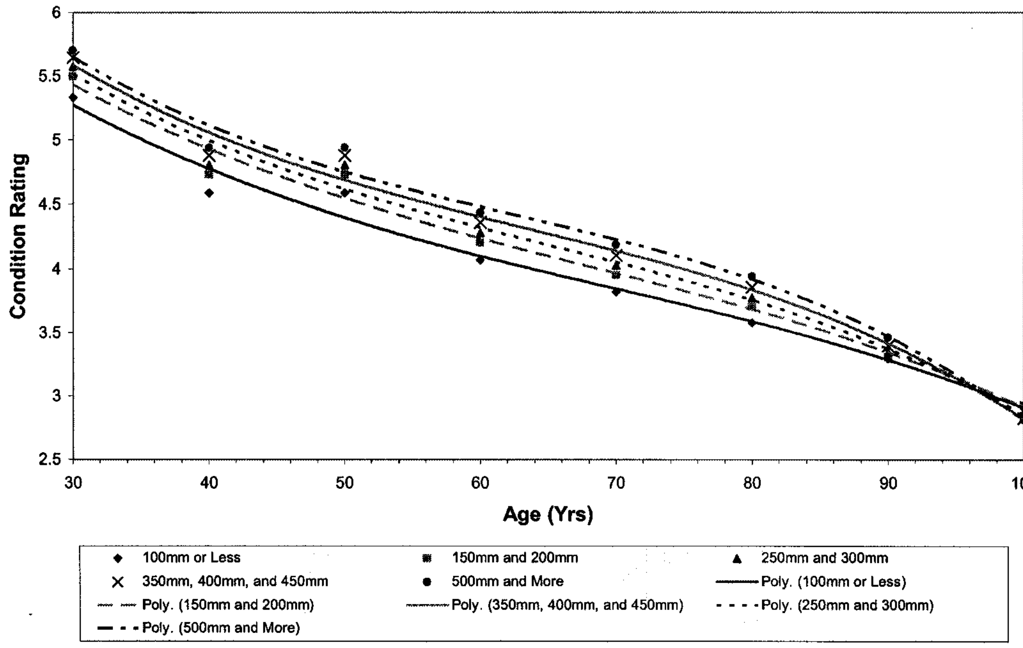


Figure E-51 CI-A: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

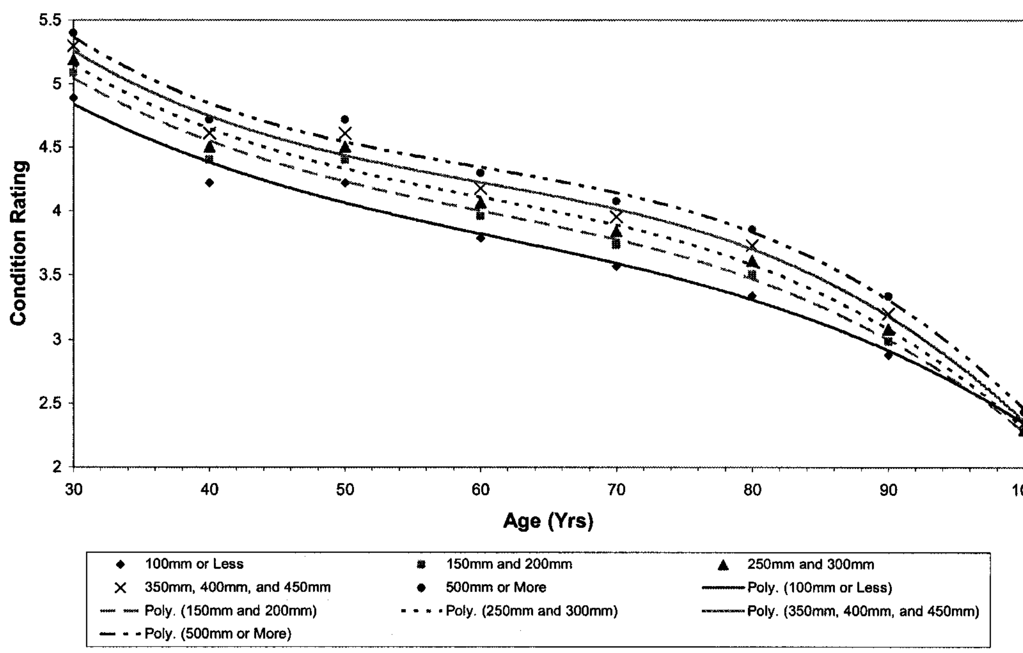


Figure E-52 CI-A: C-factor (40) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

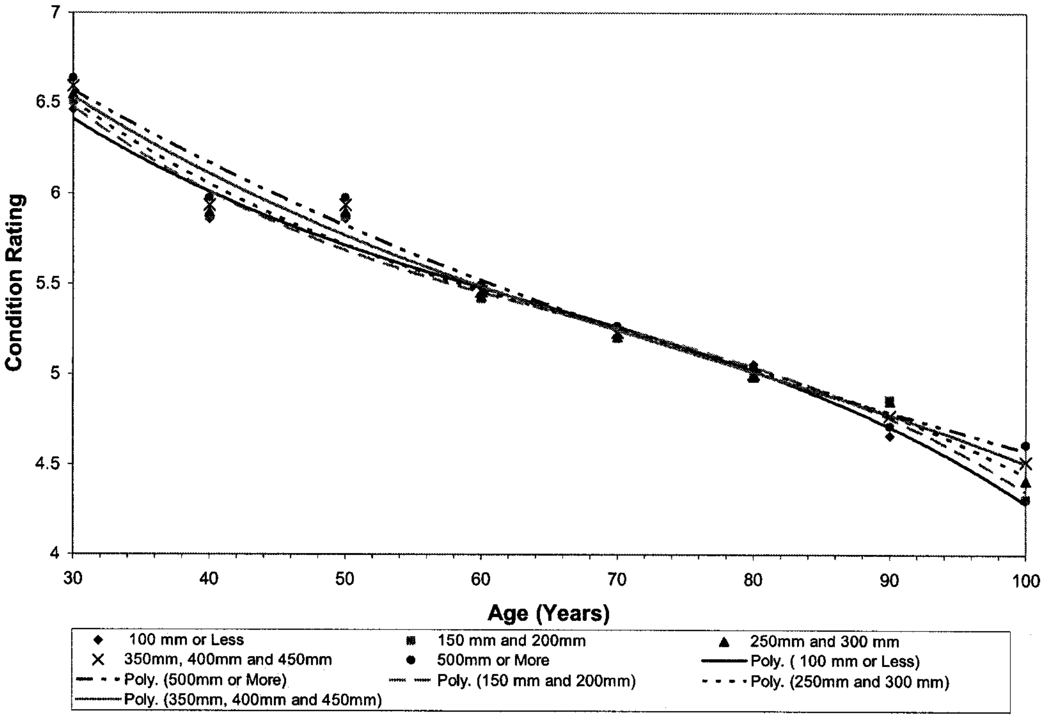


Figure E-53 CI-A: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

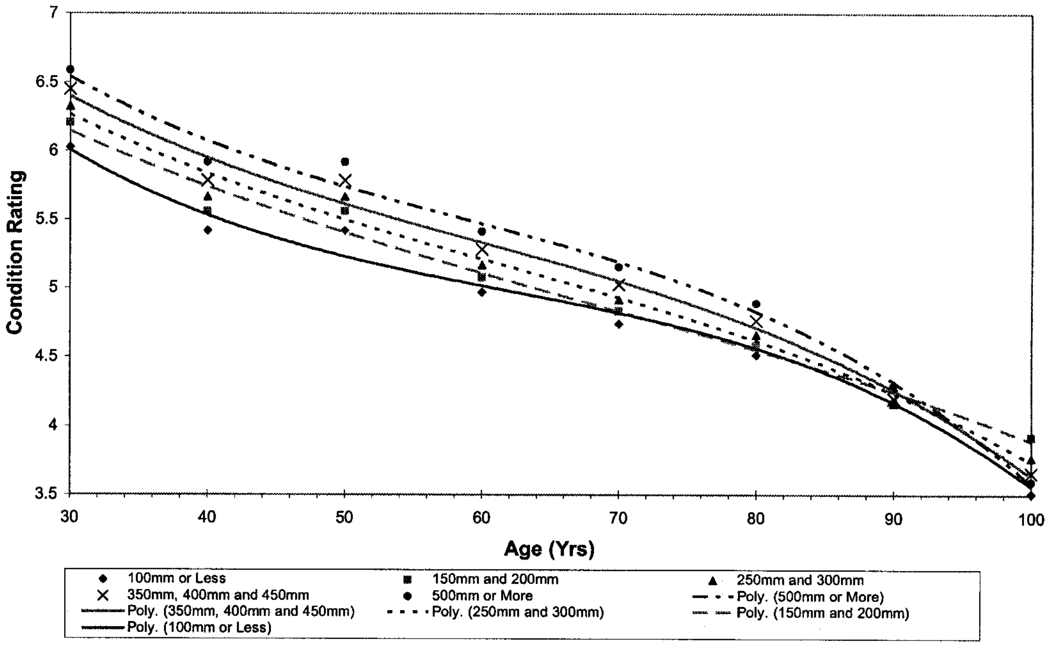


Figure E-54 CI-A: C-factor (120) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

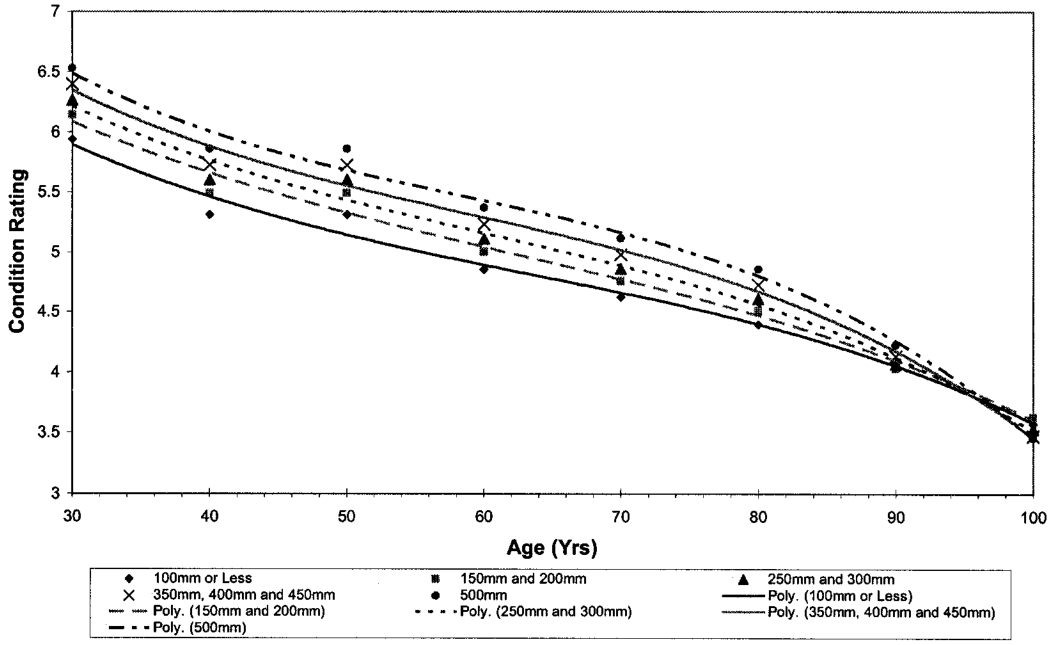


Figure E-55 CI-A: C-factor (100) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

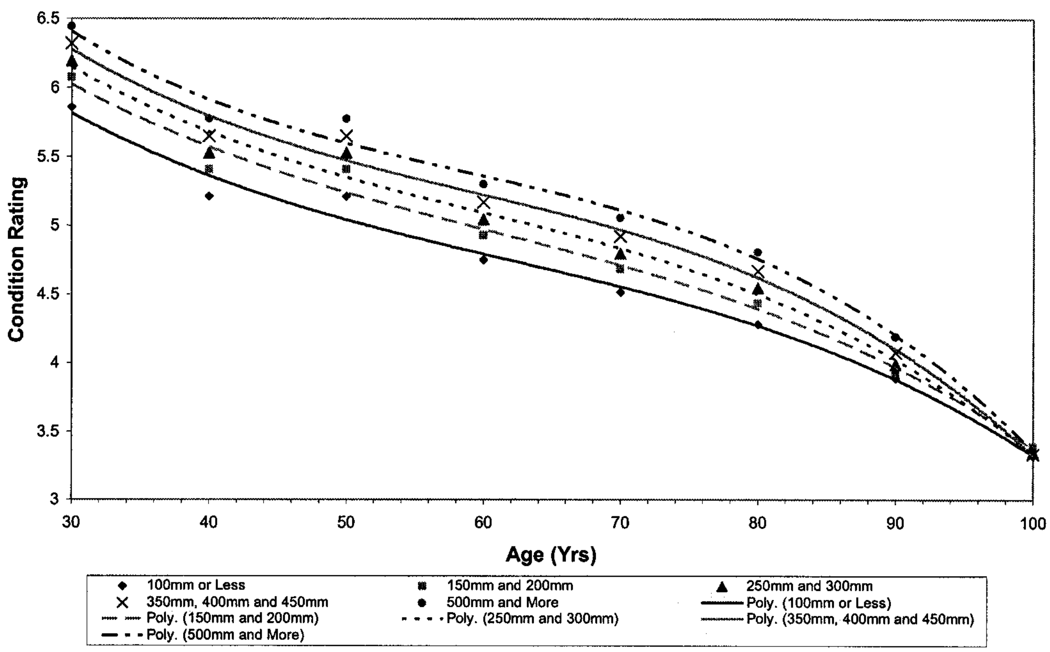


Figure E-56 CI-A: C-factor (80) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

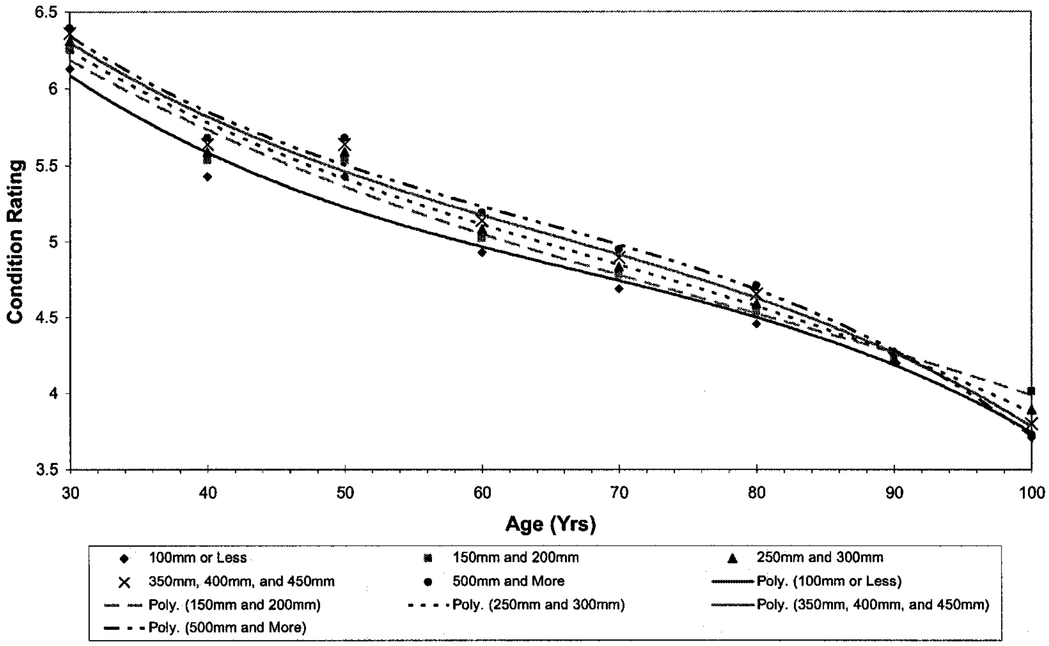


Figure E-57 CI-A: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

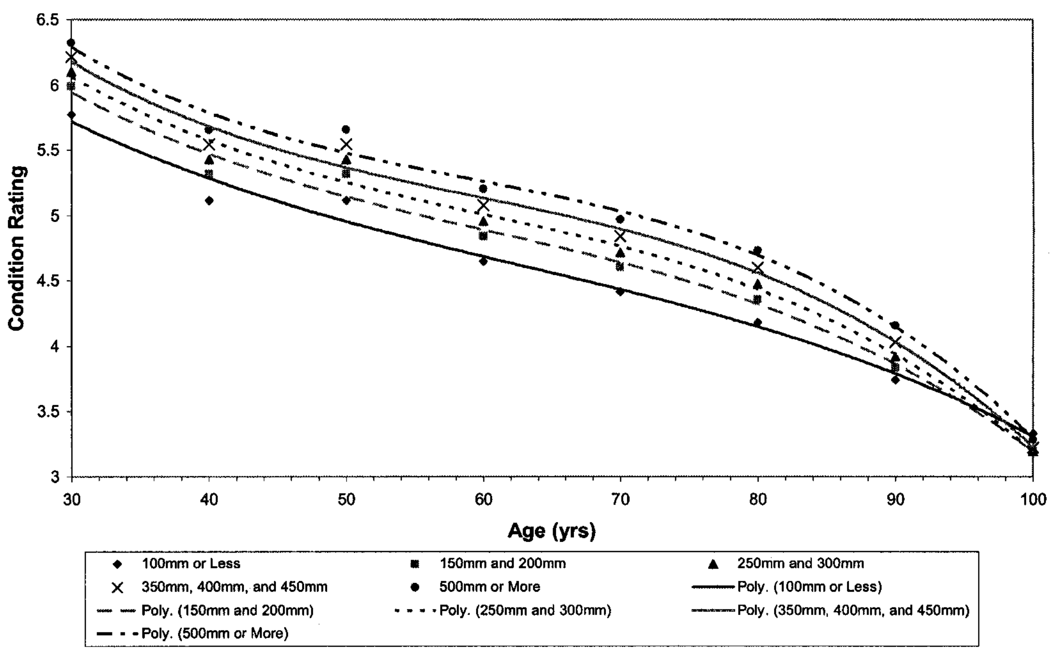


Figure E-58 CI-A: C-factor (60) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

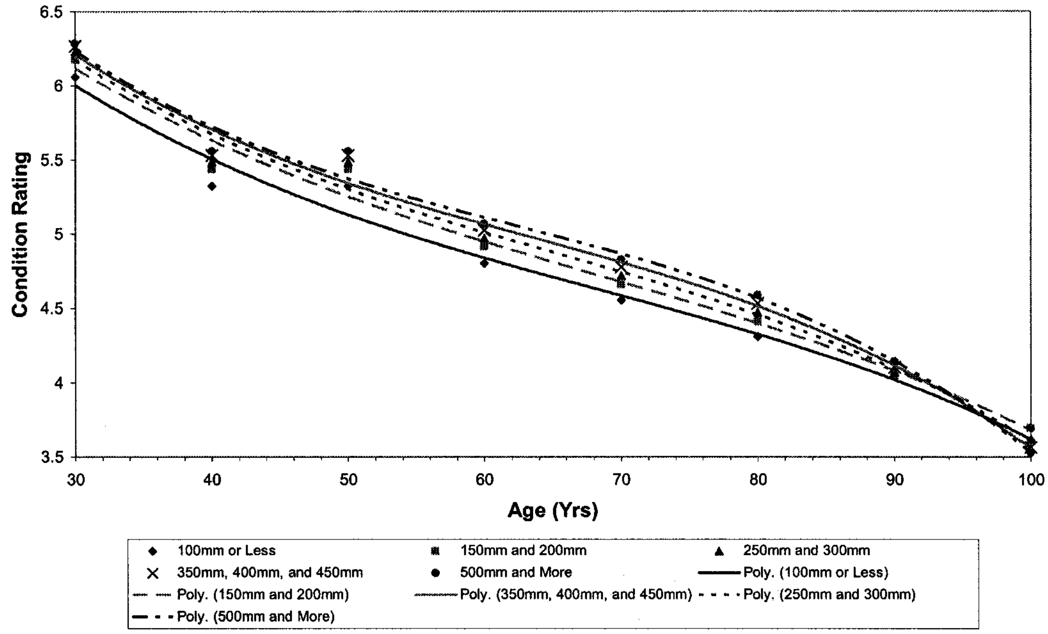


Figure E-59 CI-A: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

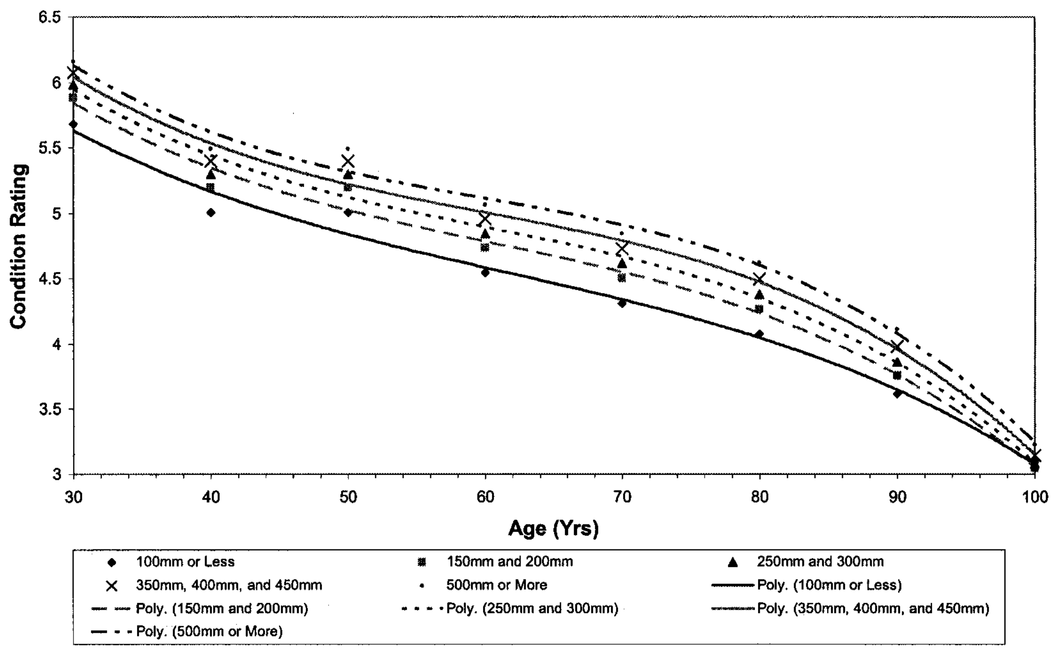


Figure E-60 CI-A: C-factor (40) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

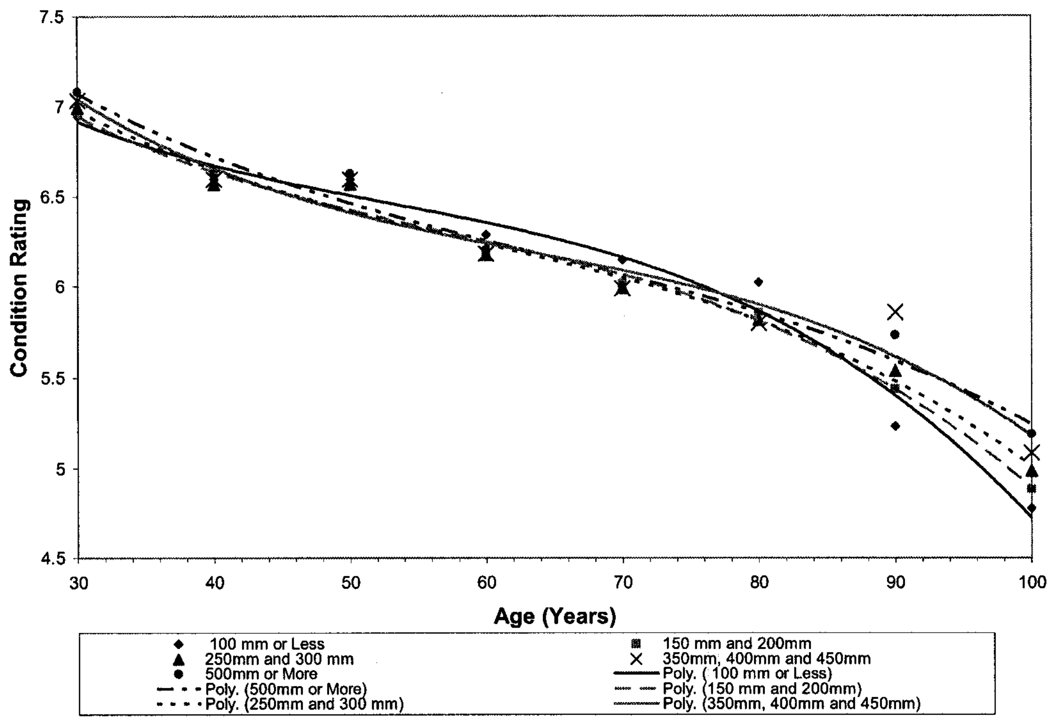


Figure E-61 CI-A: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

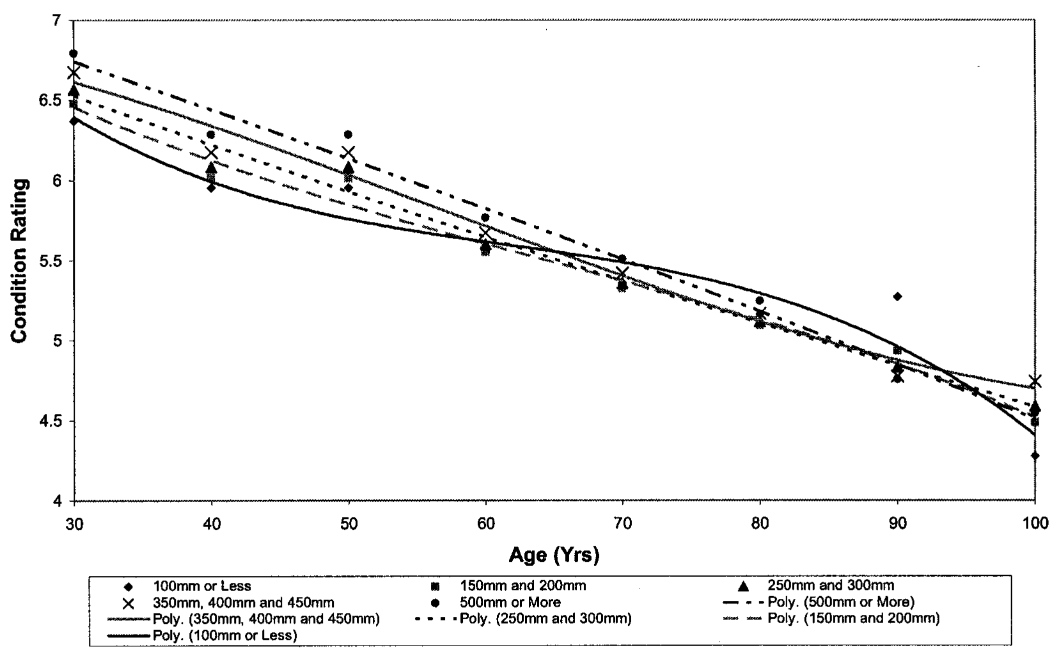


Figure E-62 CI-A: C-factor (120) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

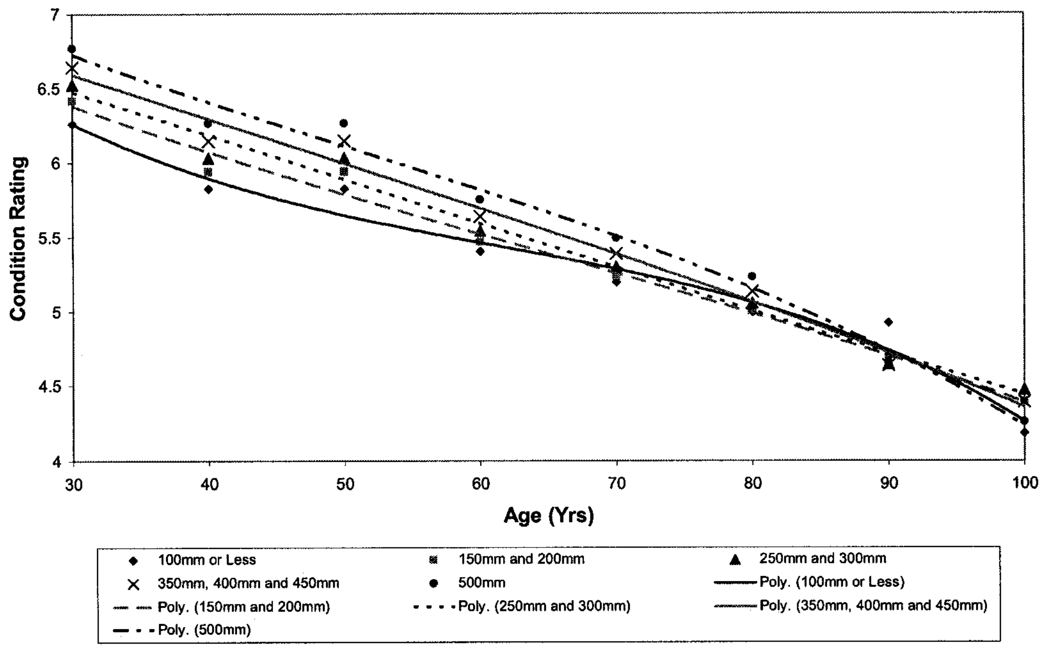


Figure E-63 CI-A: C-factor (100) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

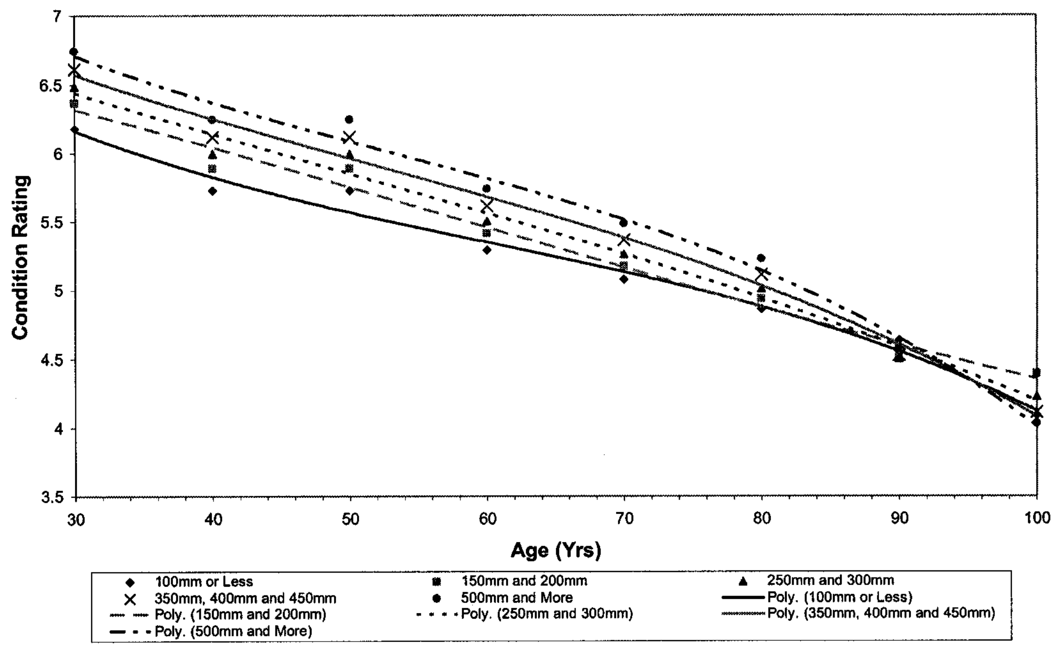


Figure E-64 CI-A: C-factor (80) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

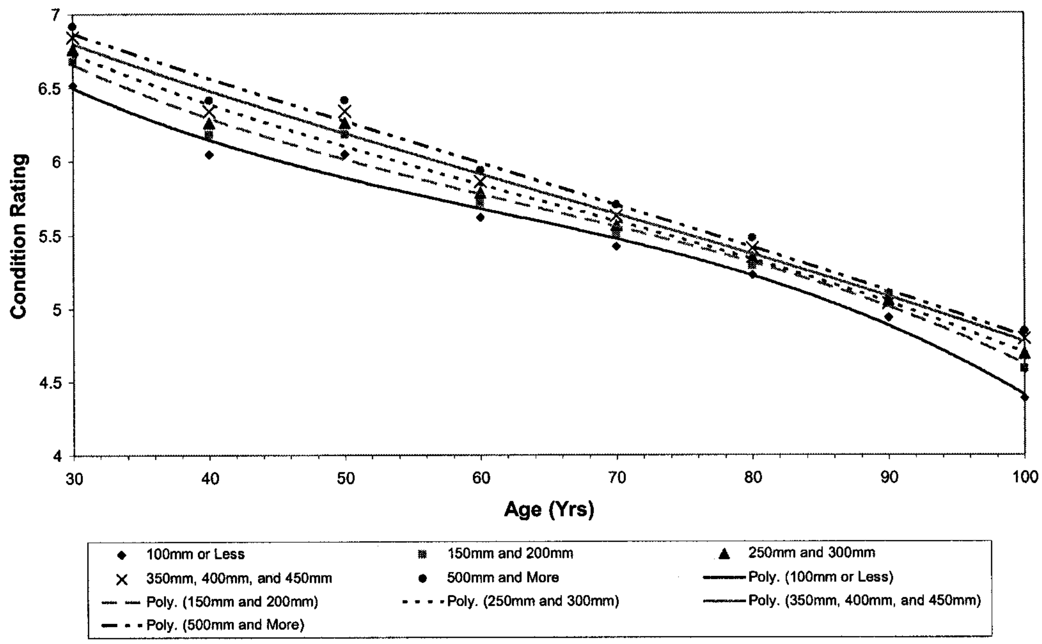


Figure E-65 CI-A: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

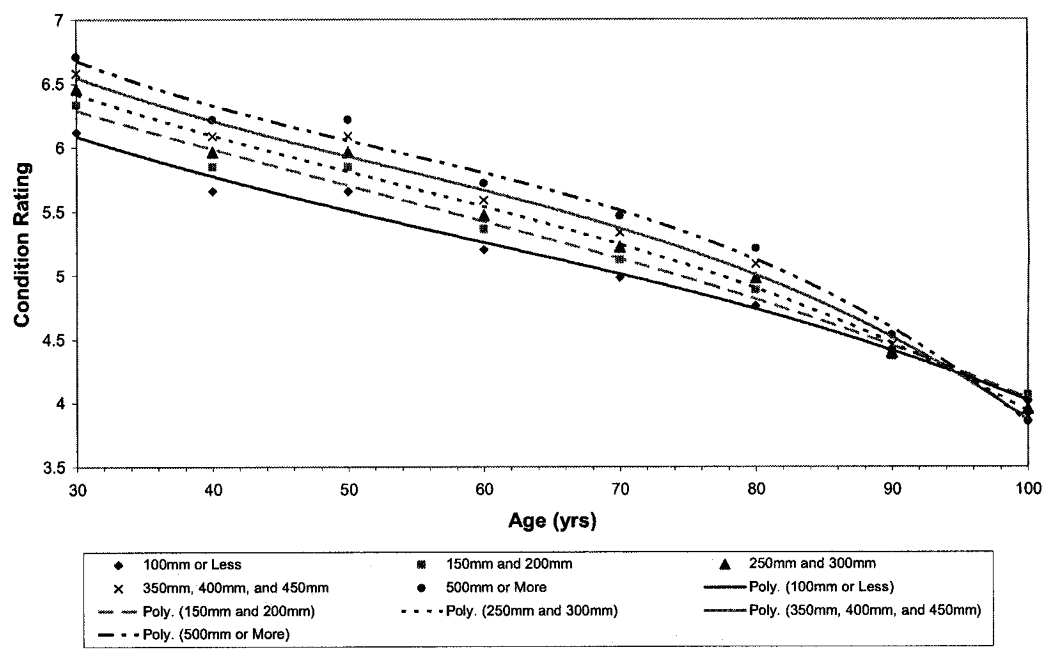


Figure E-66 CI-A: C-factor (60) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

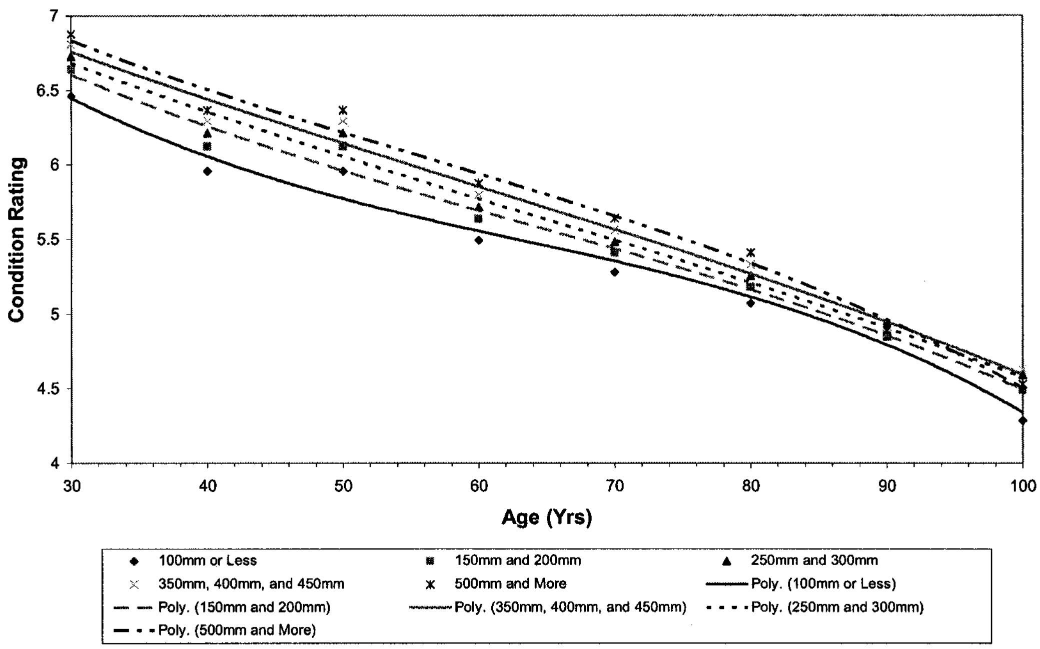


Figure E-67 CI-A: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

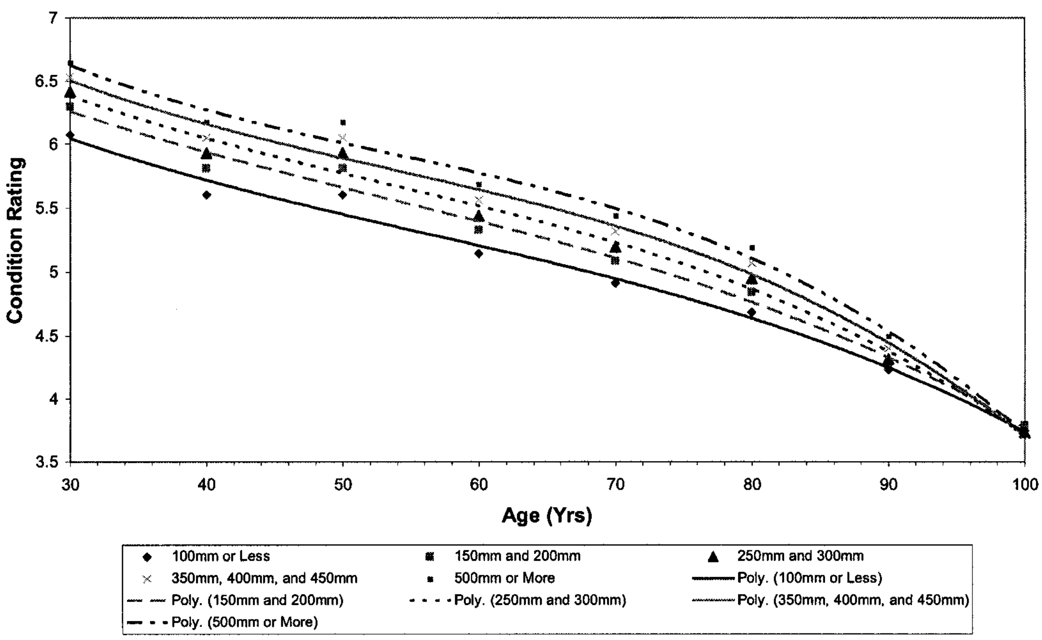


Figure E-68 CI-A: C-factor (40) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

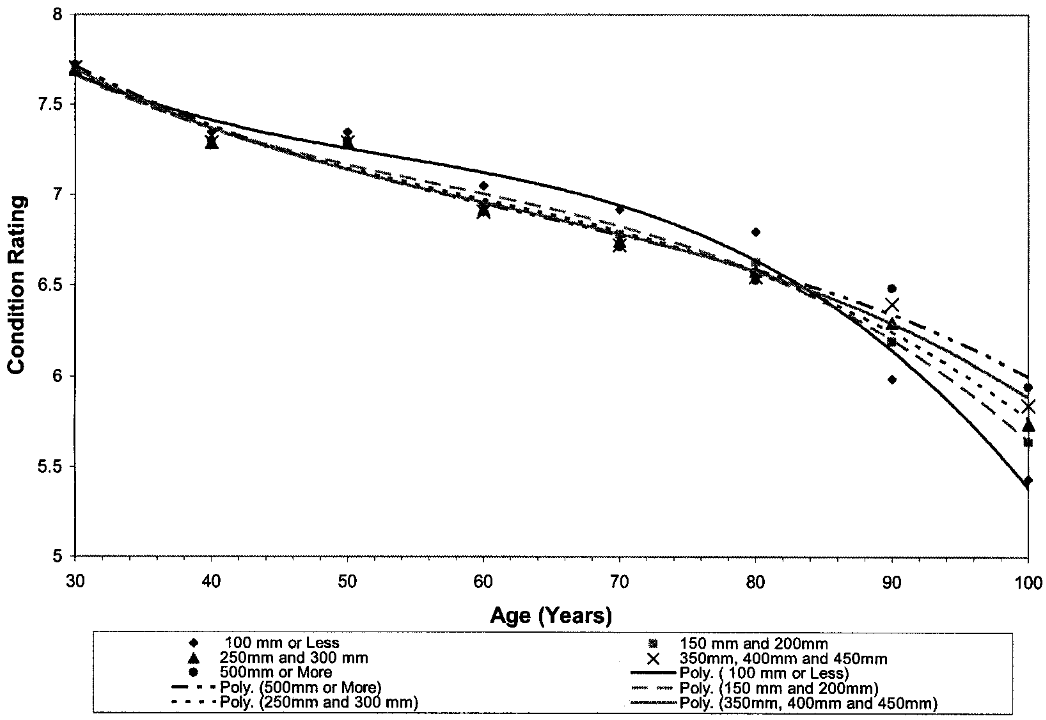


Figure E-69 CI-A: C-factor (120)- Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

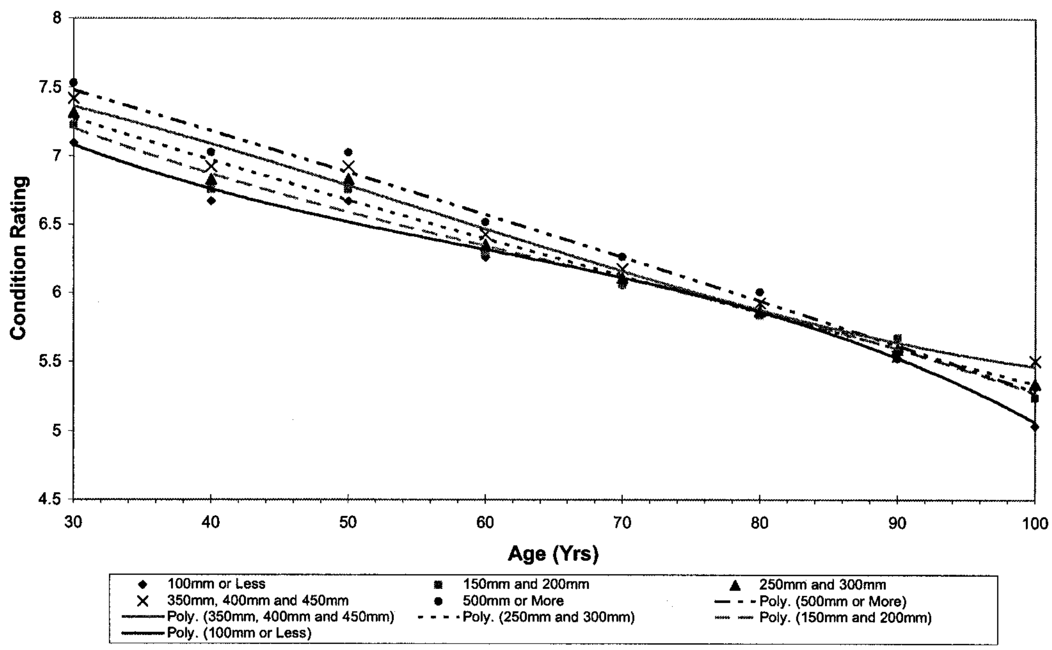


Figure E-70 CI-A: C-factor (120) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

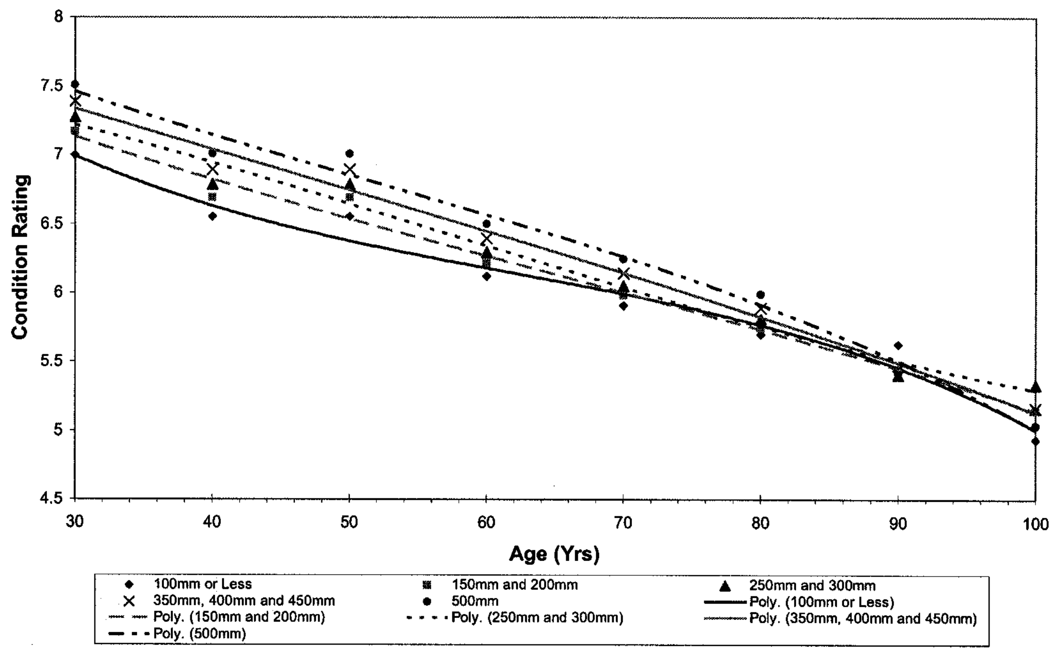


Figure E-71 CI-A: C-factor (100) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

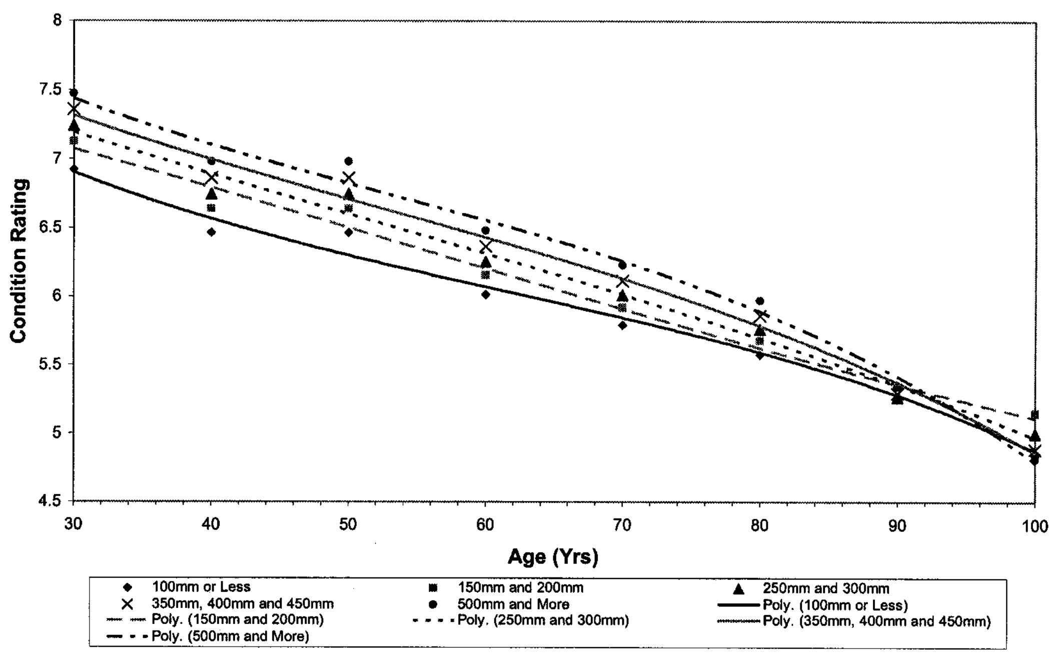


Figure E-72 CI-A: C-factor (80) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

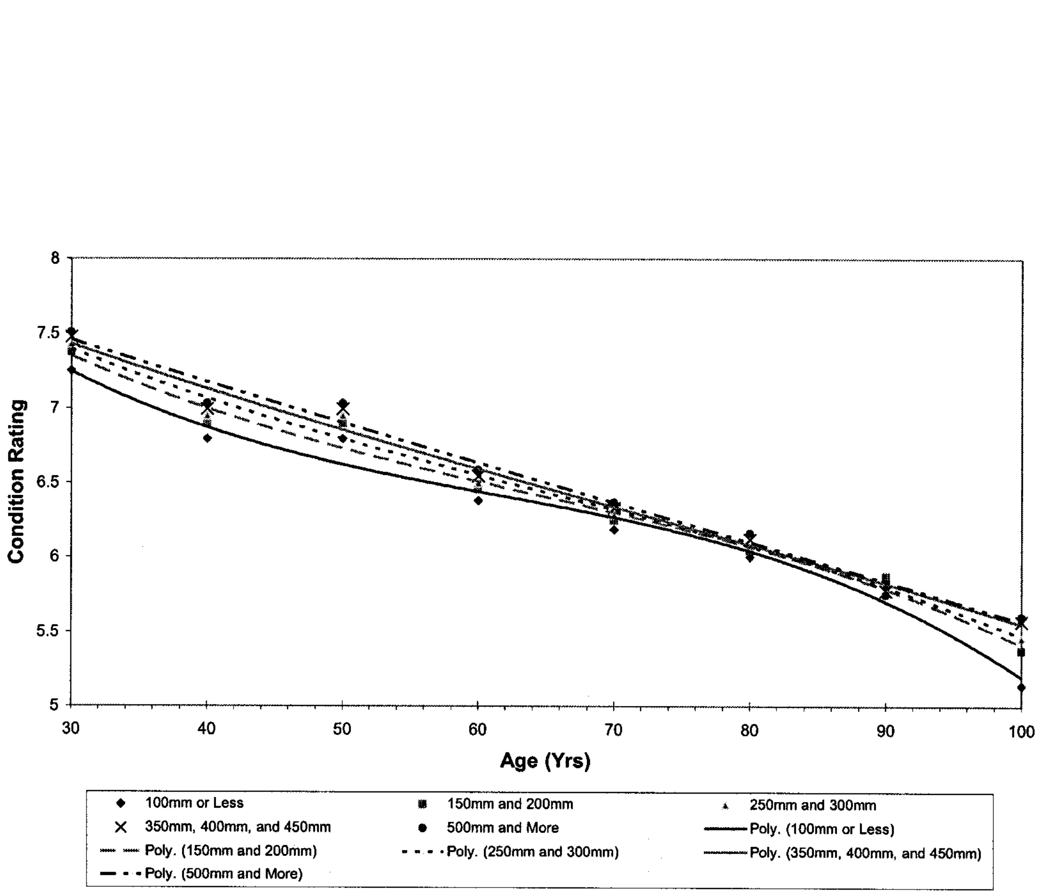


Figure E-73 CI-A: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

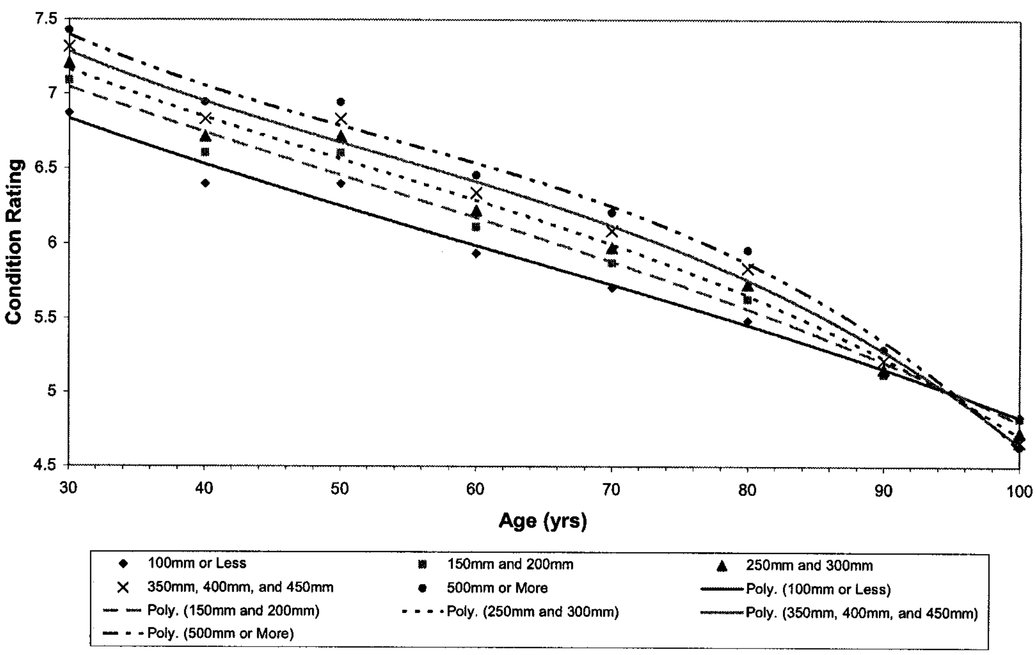


Figure E-74 CI-A: C-factor (60) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

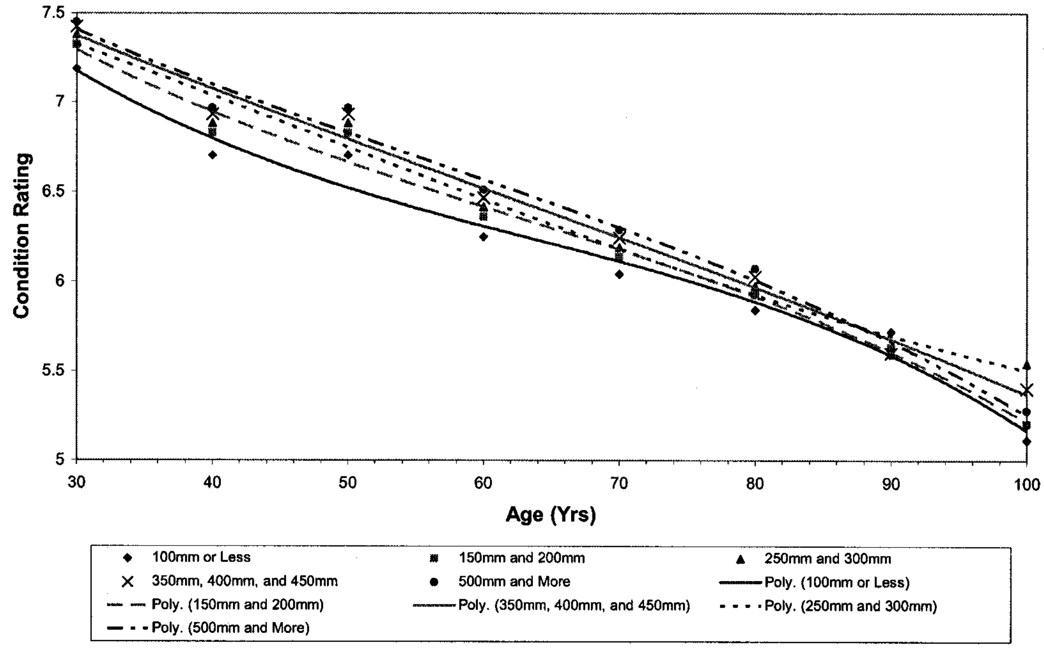


Figure E-75 CI-A: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

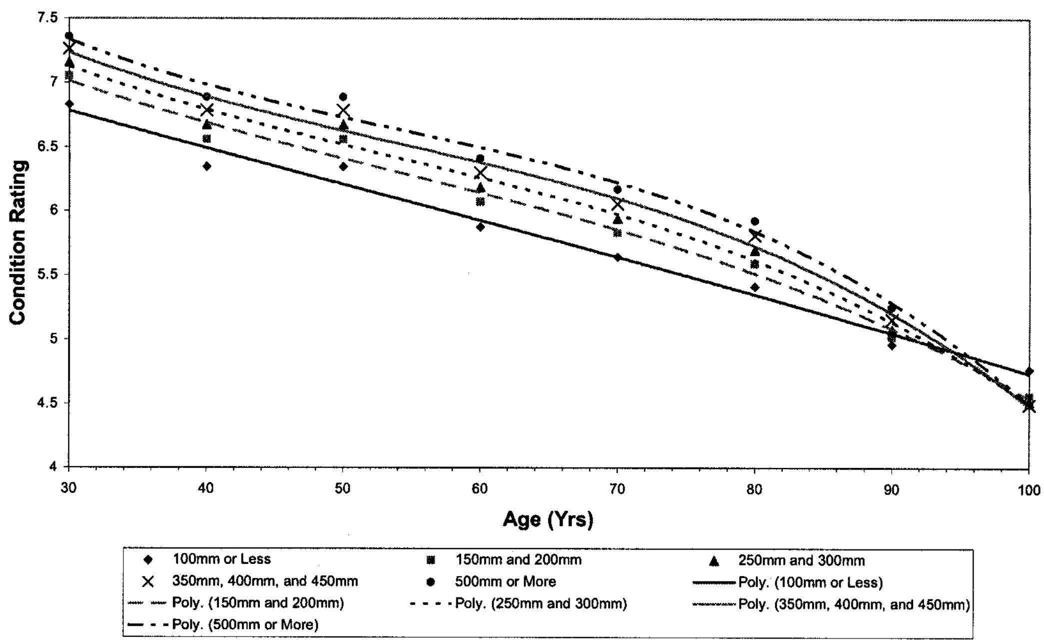


Figure E-76 CI-A: C-factor (40) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

E.3. CAST IRON PREDICTION CURVES (Before WW II)

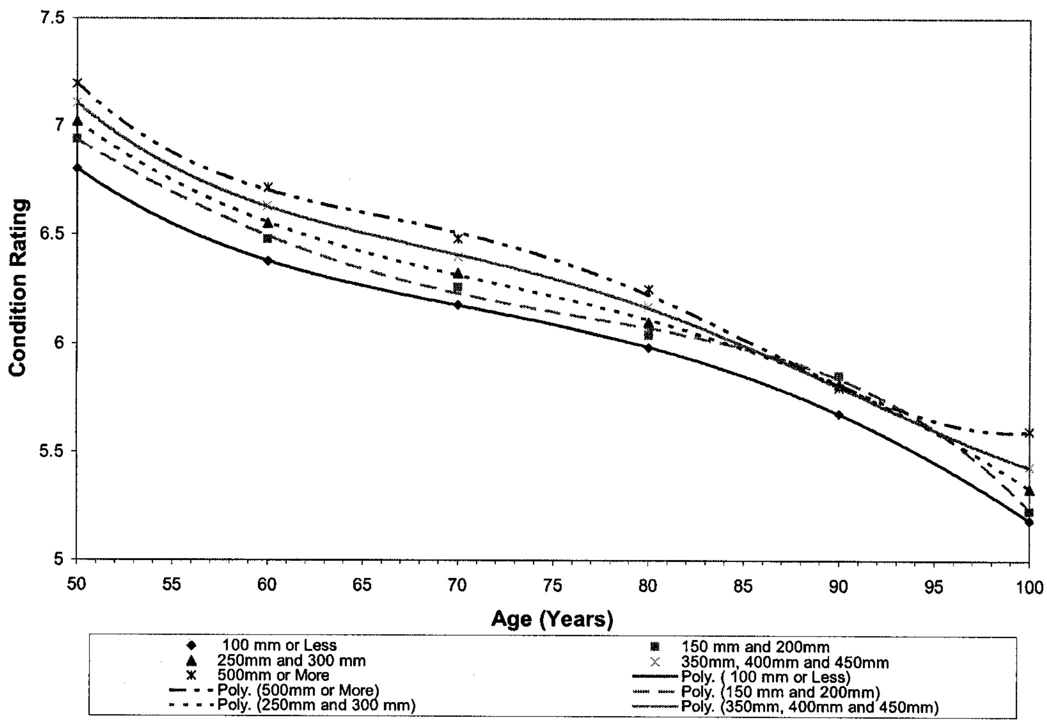


Figure E-77 CI: C-factor (120) -Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

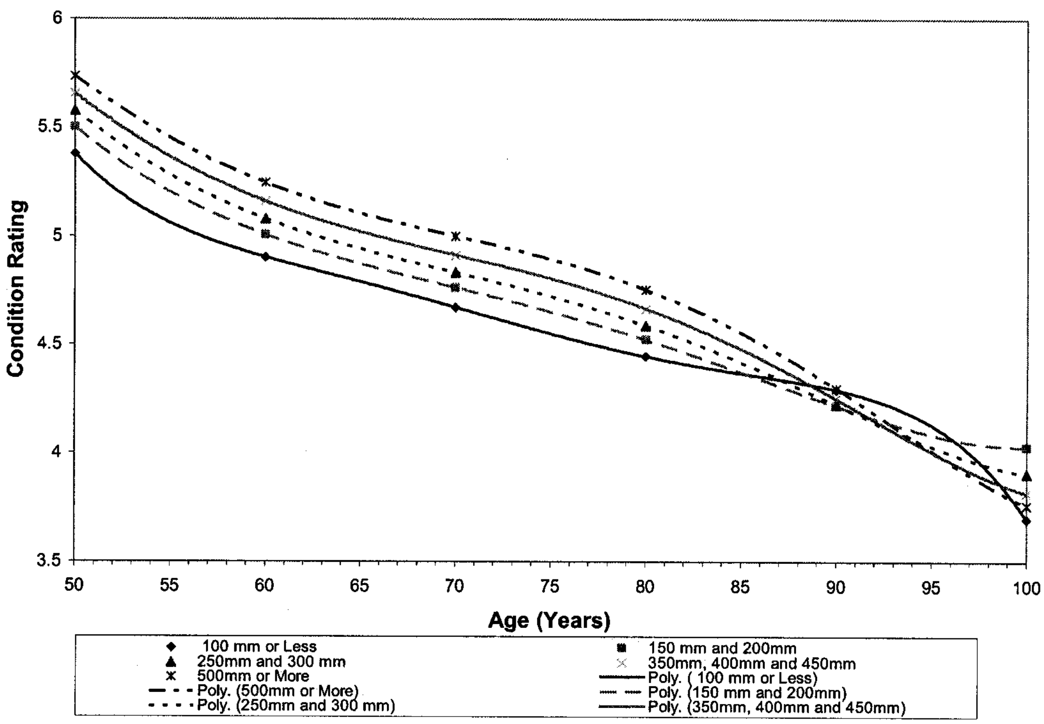


Figure E-78 CI: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

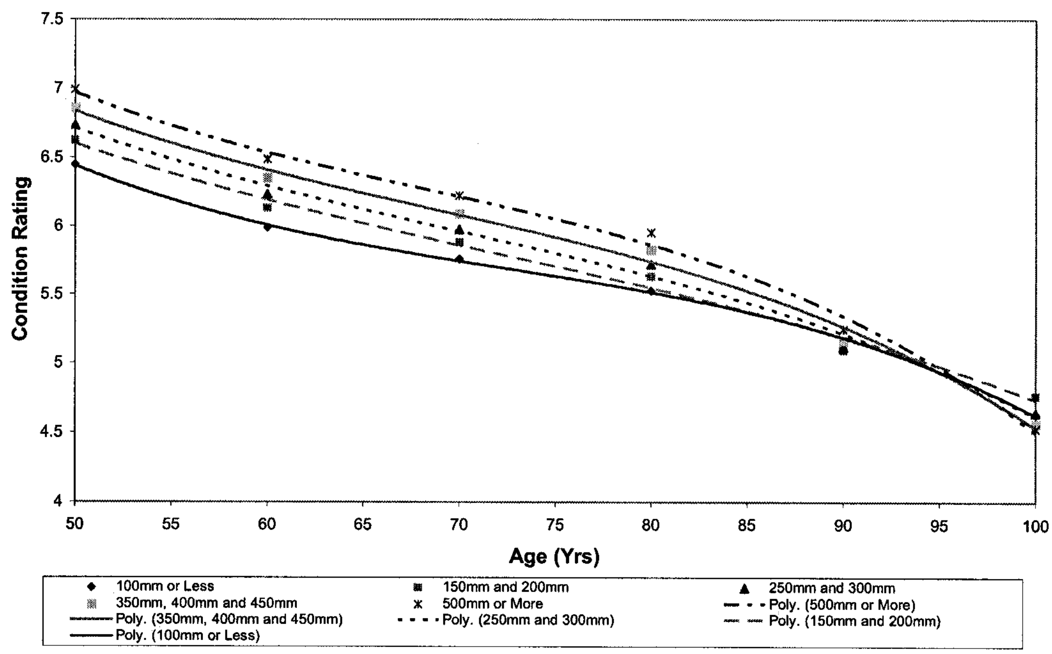


Figure E-79 CI: C-factor (120) -Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

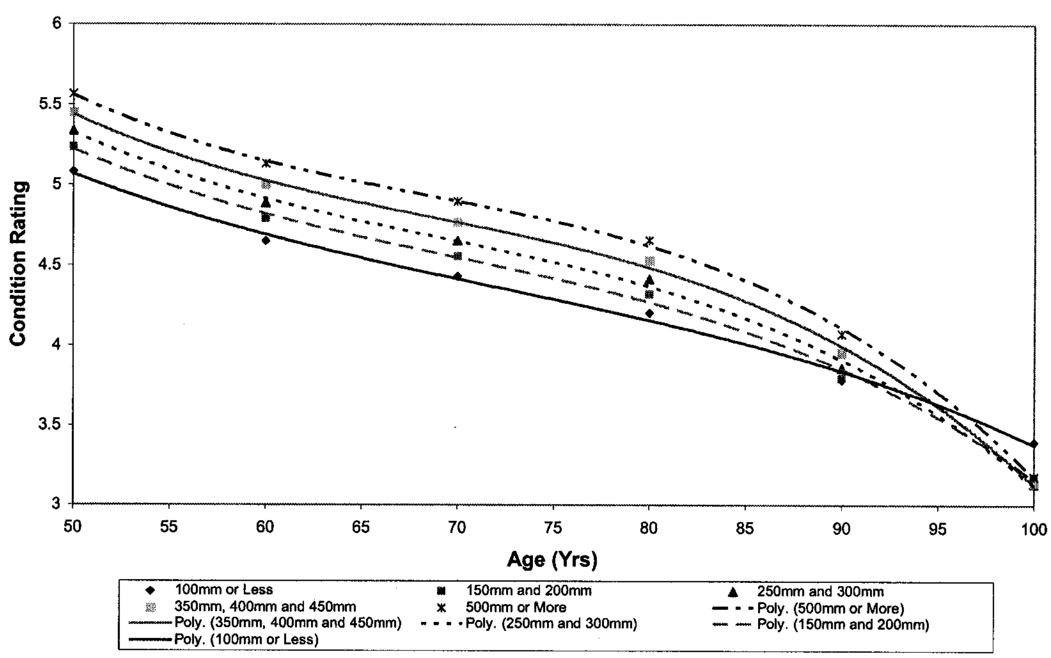


Figure E-80 CI: C-factor (120) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

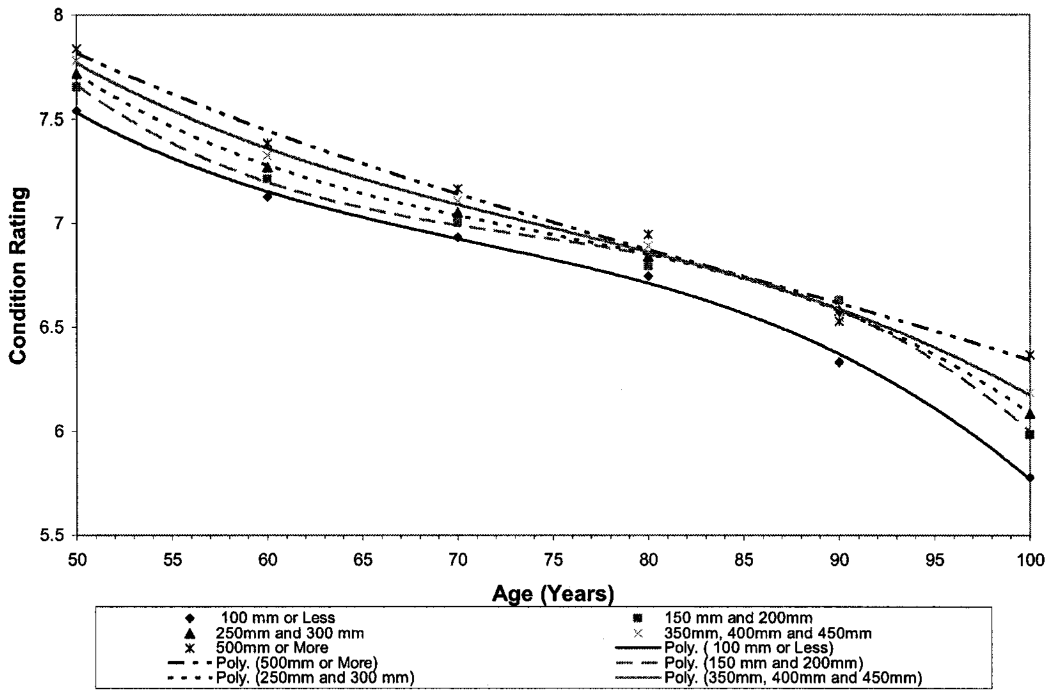


Figure E-81 CI: C-factor (120) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

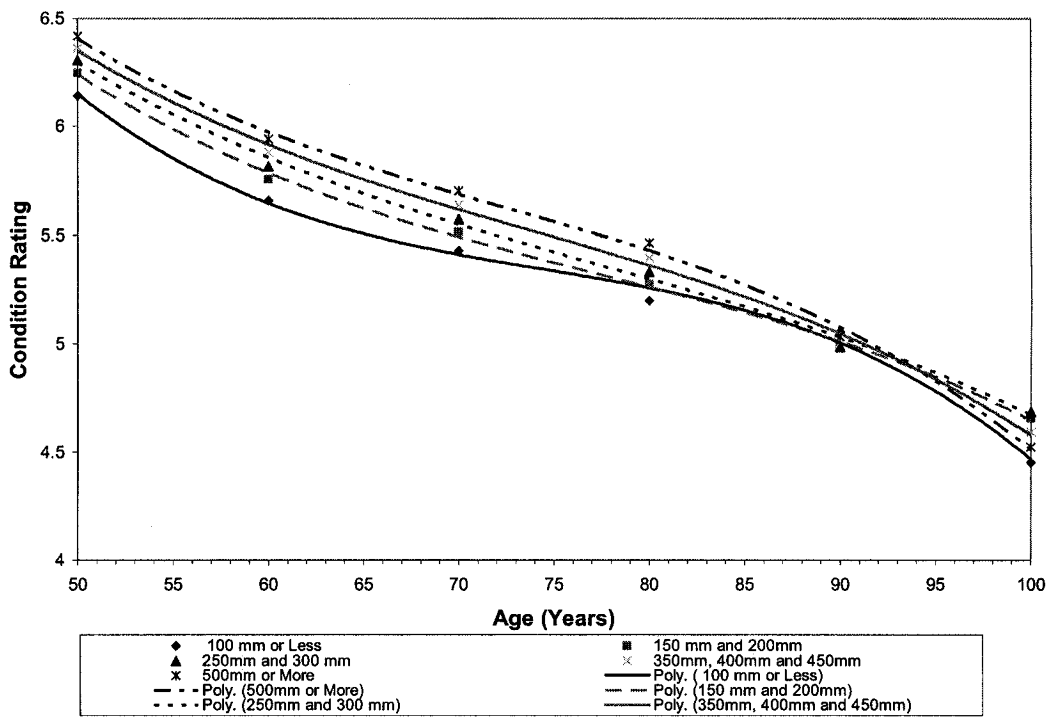


Figure E-82 CI: C-factor (120) -Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

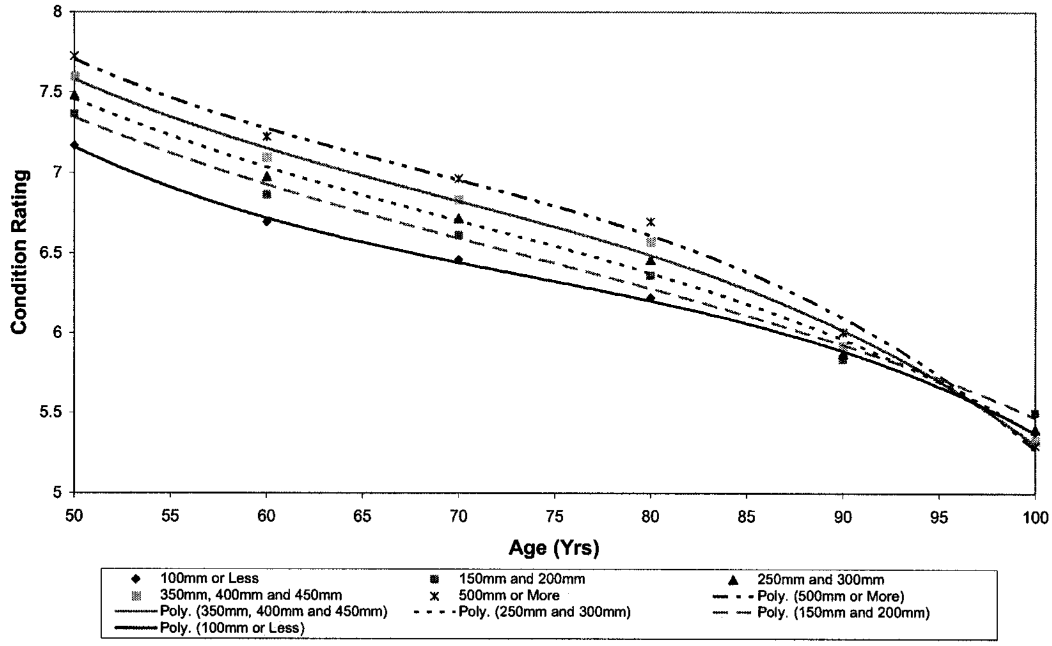


Figure E-83 CI: C-factor (120) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

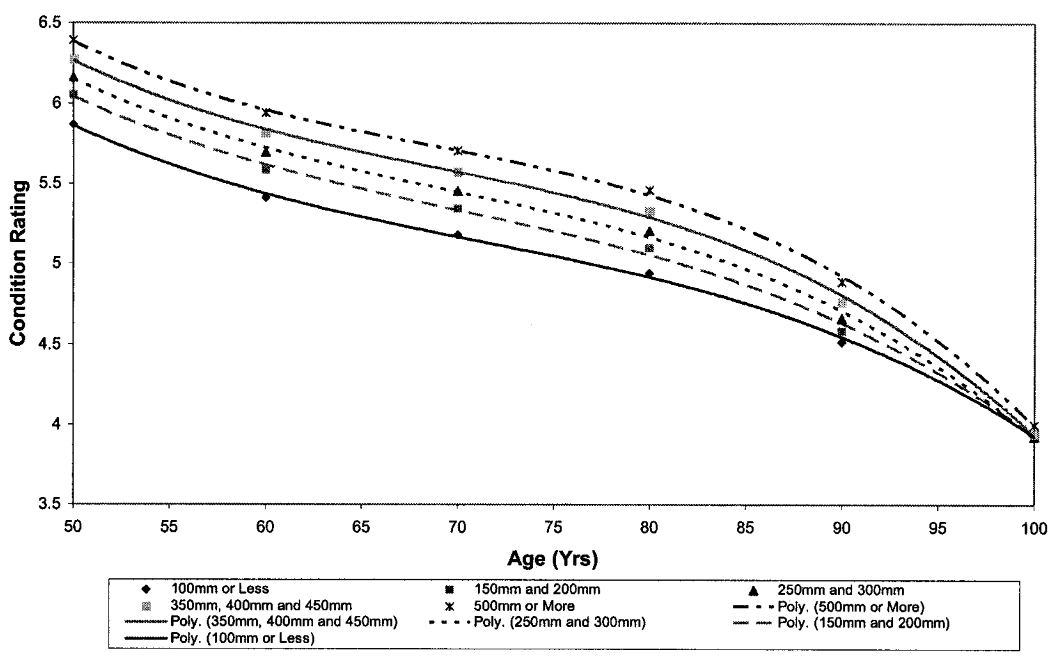


Figure E-84 CI: C-factor (120) -Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

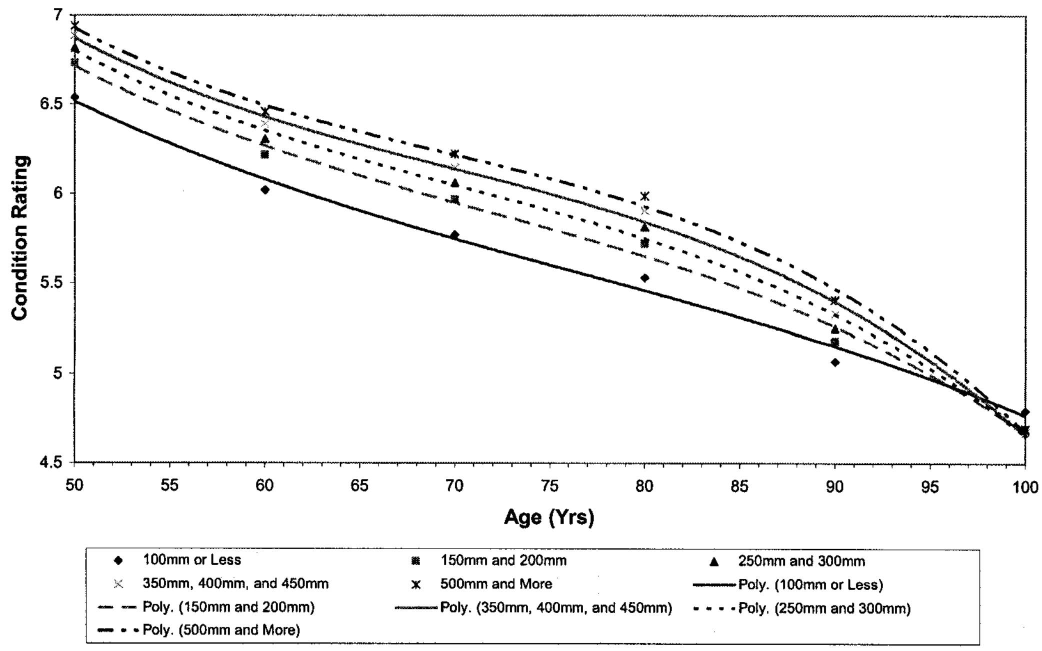


Figure E-85 CI: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (0.1)

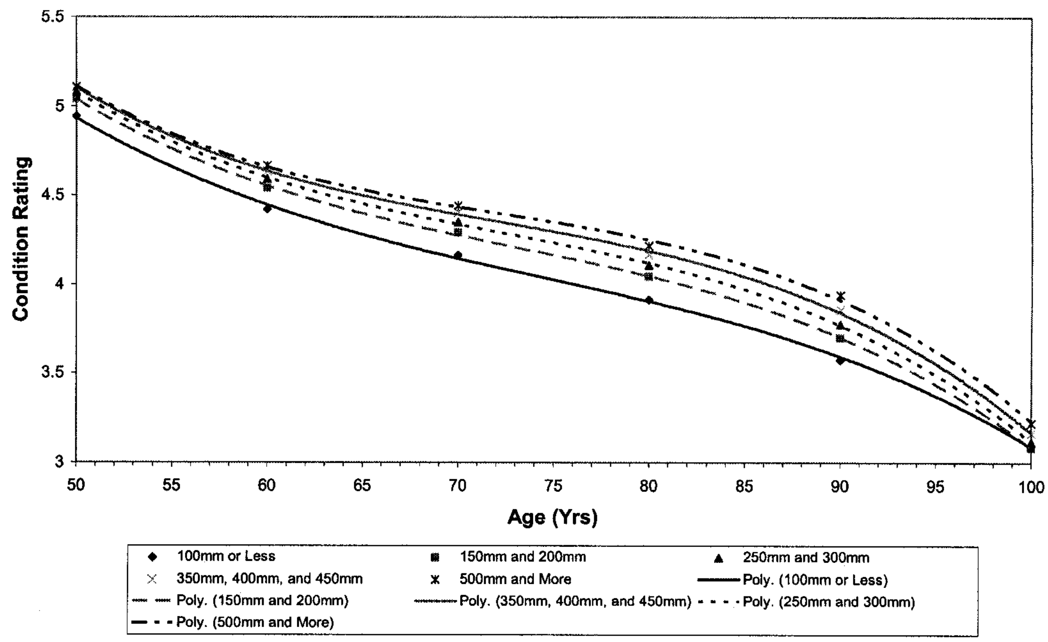


Figure E-86 CI: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

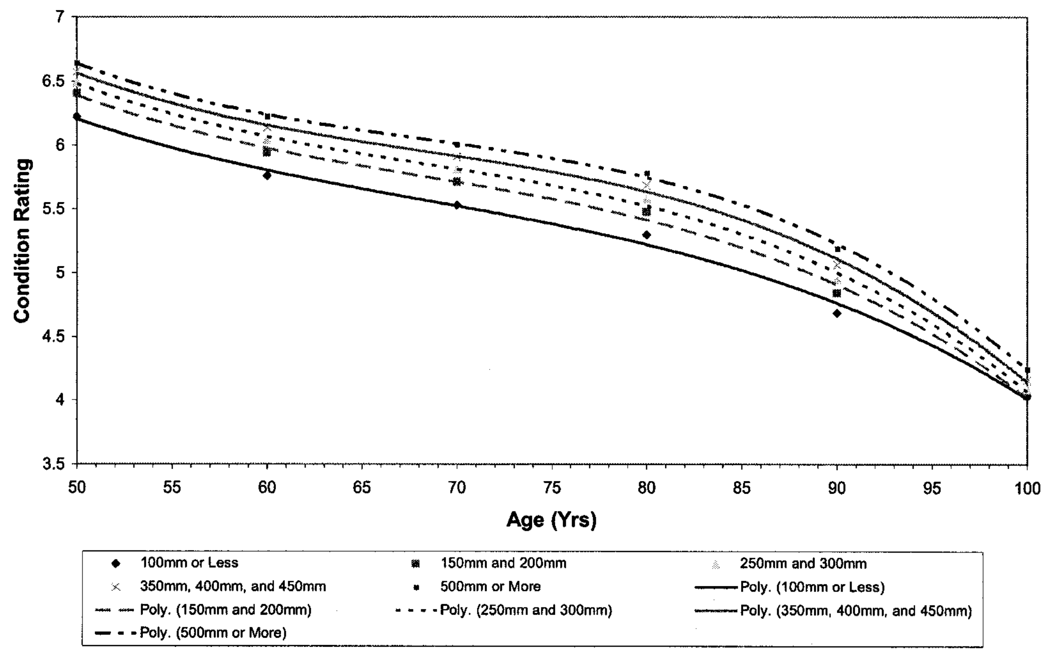


Figure E-87 CI: C-factor (40) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (0.1)

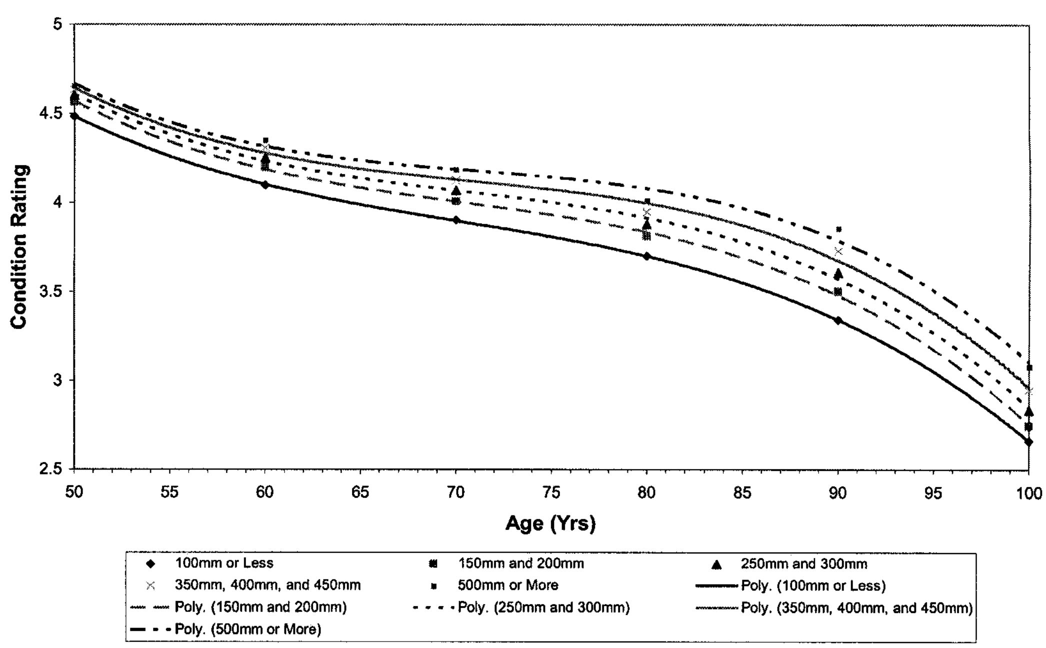


Figure E-88 CI: C-factor (40) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

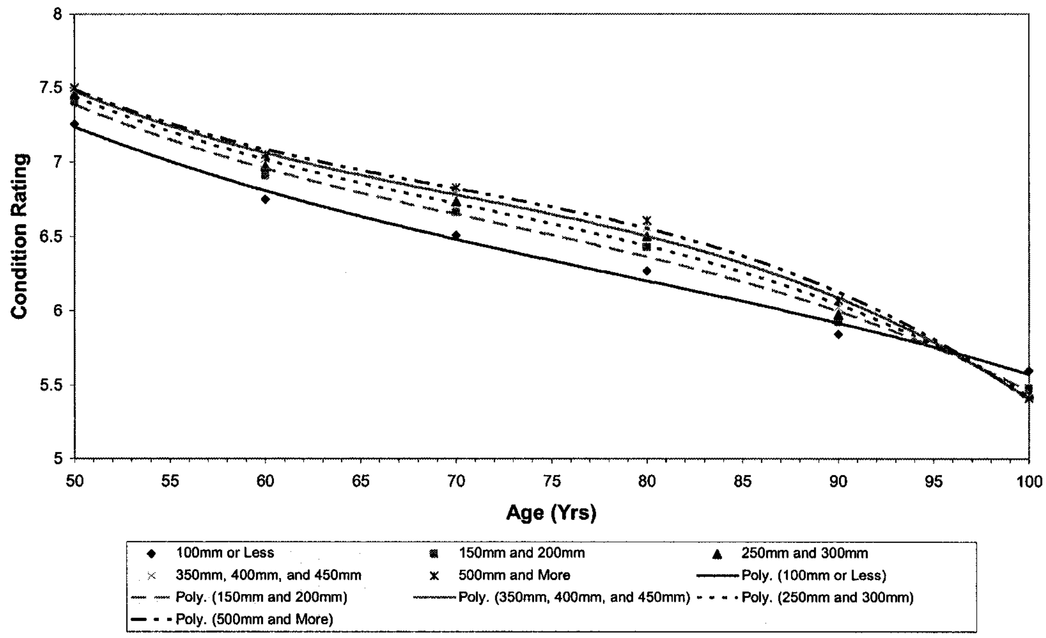


Figure E-89 CI: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (0.1)

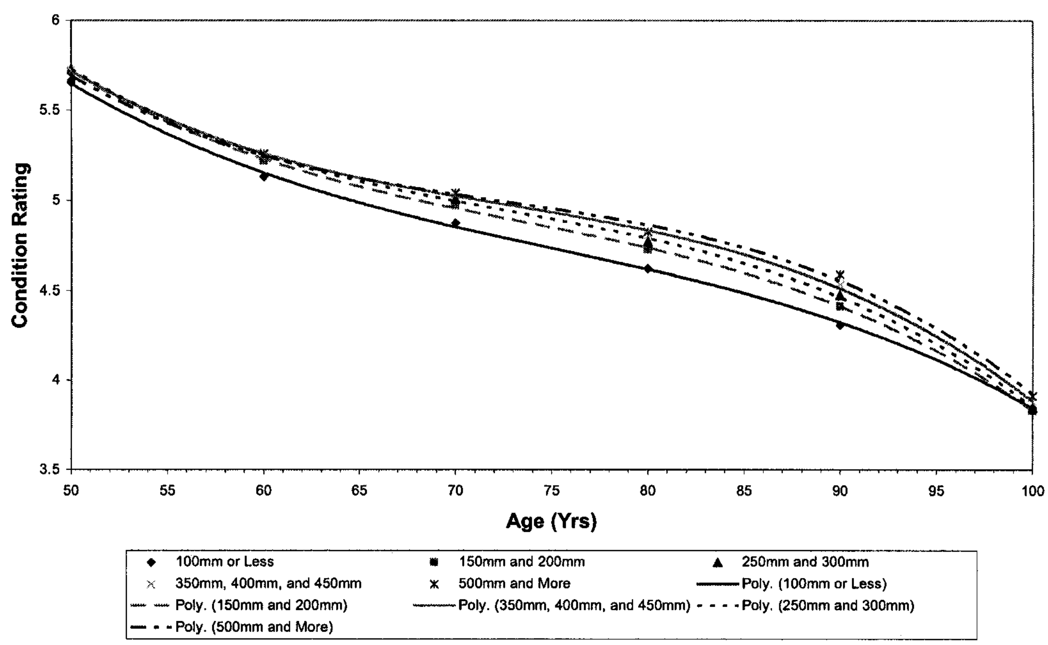


Figure E-90 CI: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

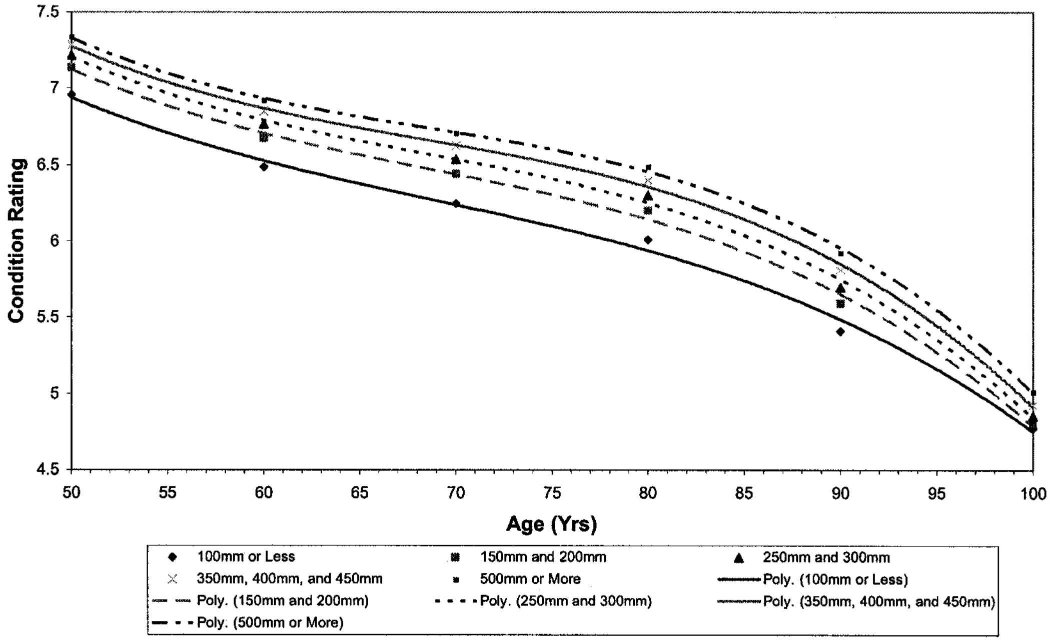


Figure E-91 CI: C-factor (40) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

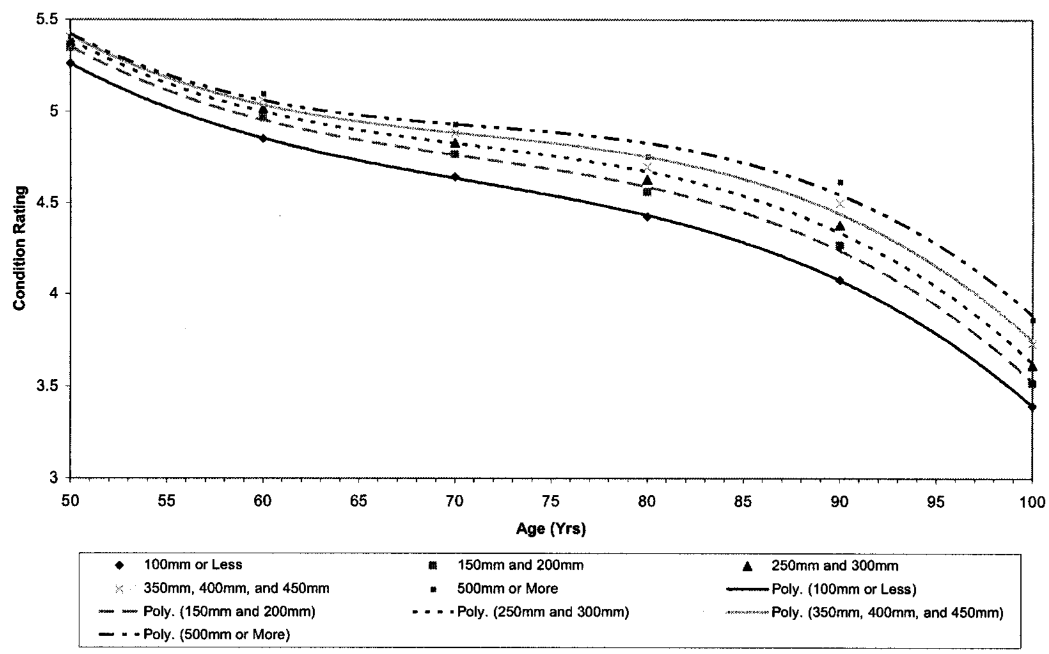


Figure E-92 CI: C-factor (40) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

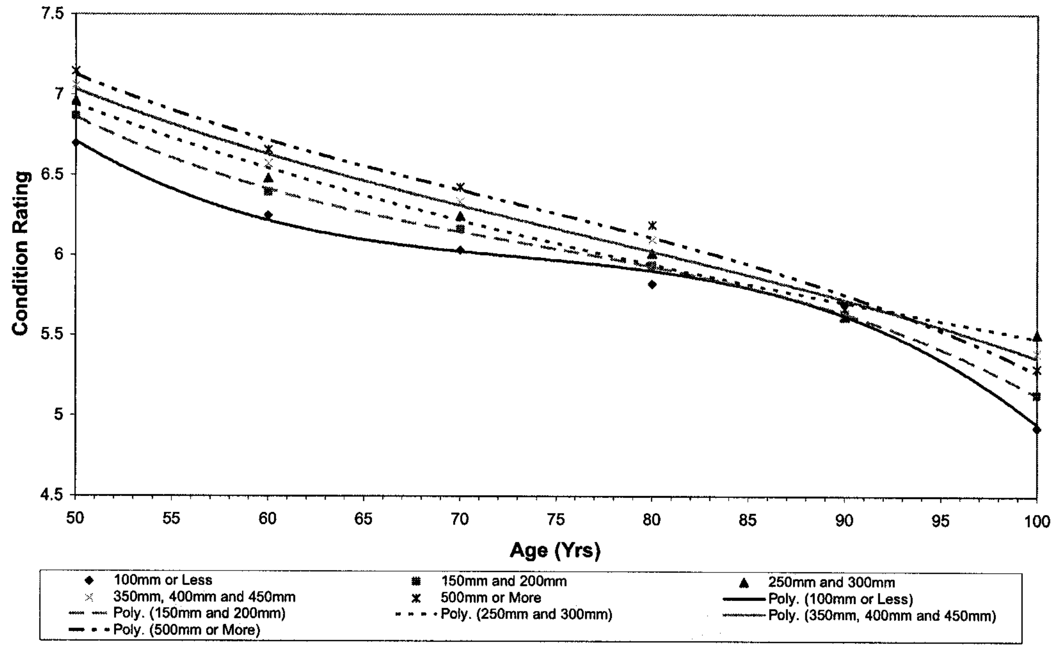


Figure E-93 CI: C-factor (100)-Cathodic Protection (Yes) - Soil Type (Clay)- Breakage Rate(0.1)

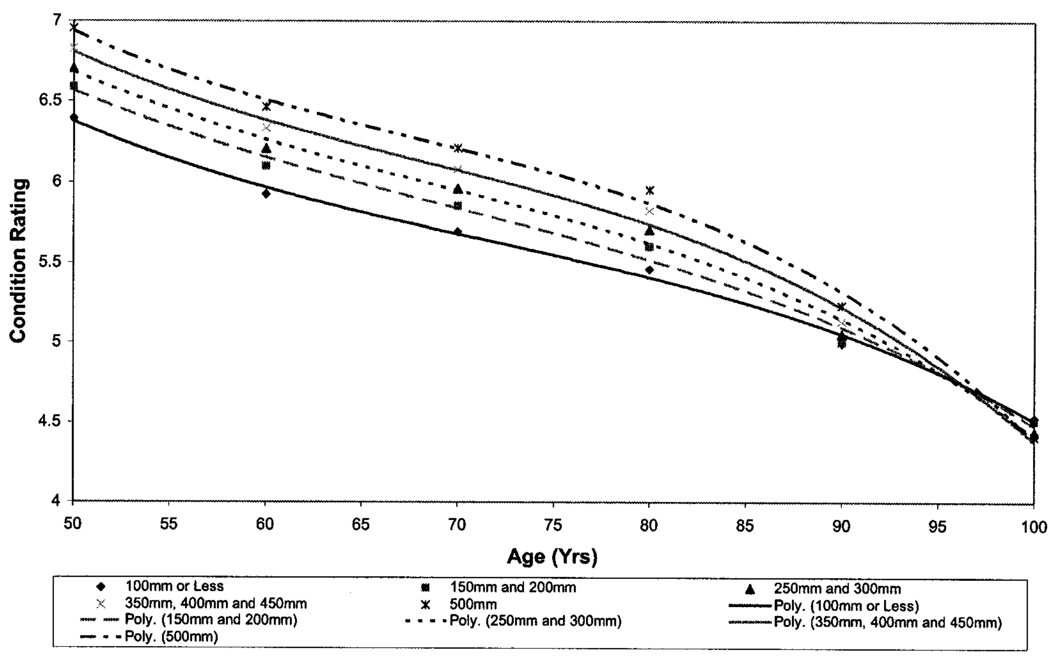


Figure E-94 CI: C-factor (100)-Cathodic Protection (No) - Soil Type (Clay)- Breakage Rate(0.1)

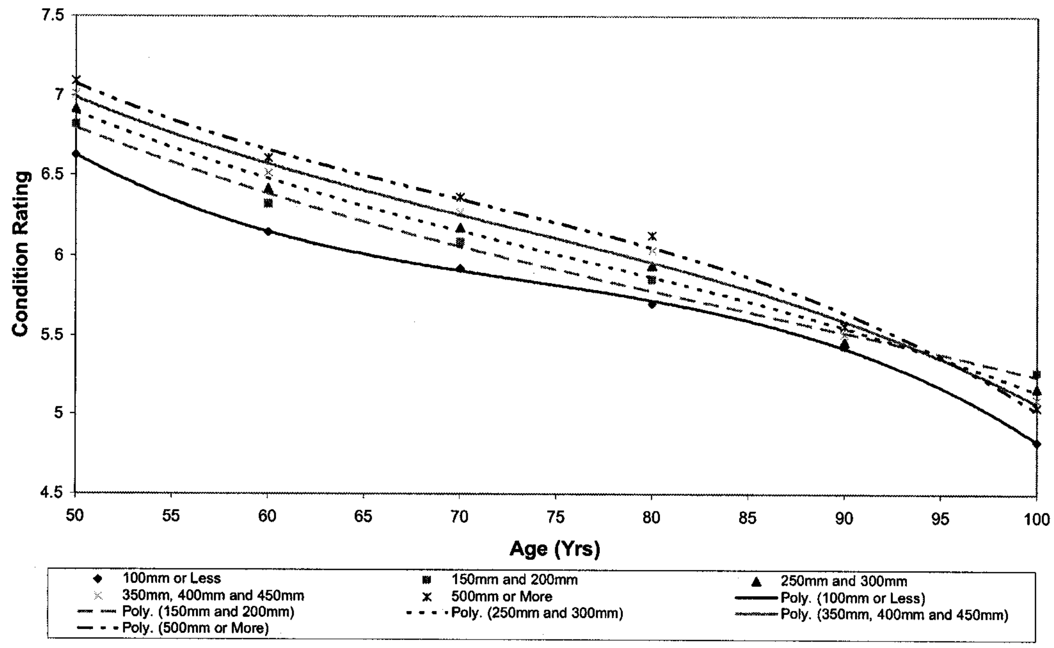


Figure E-95 CI: C-factor (80) - Cathodic Protection (Yes) - Soil Type (Clay) -Breakage Rate (0.1)

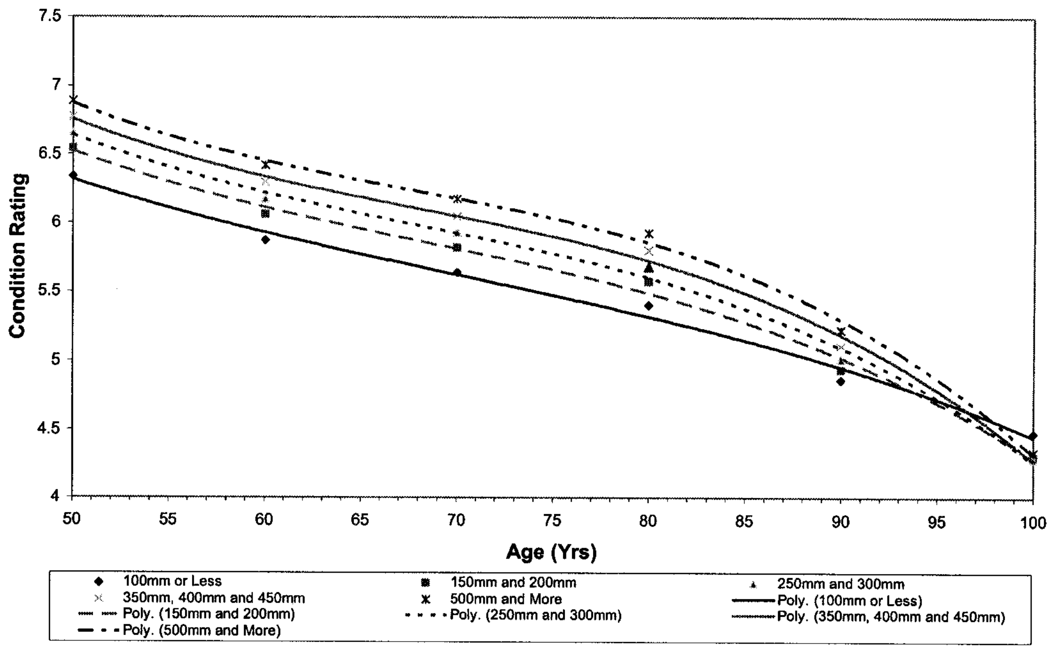


Figure E-96 CI: C-factor (80) -Cathodic Protection (No) - Soil Type (Clay) – Breakage Rate (0.1)

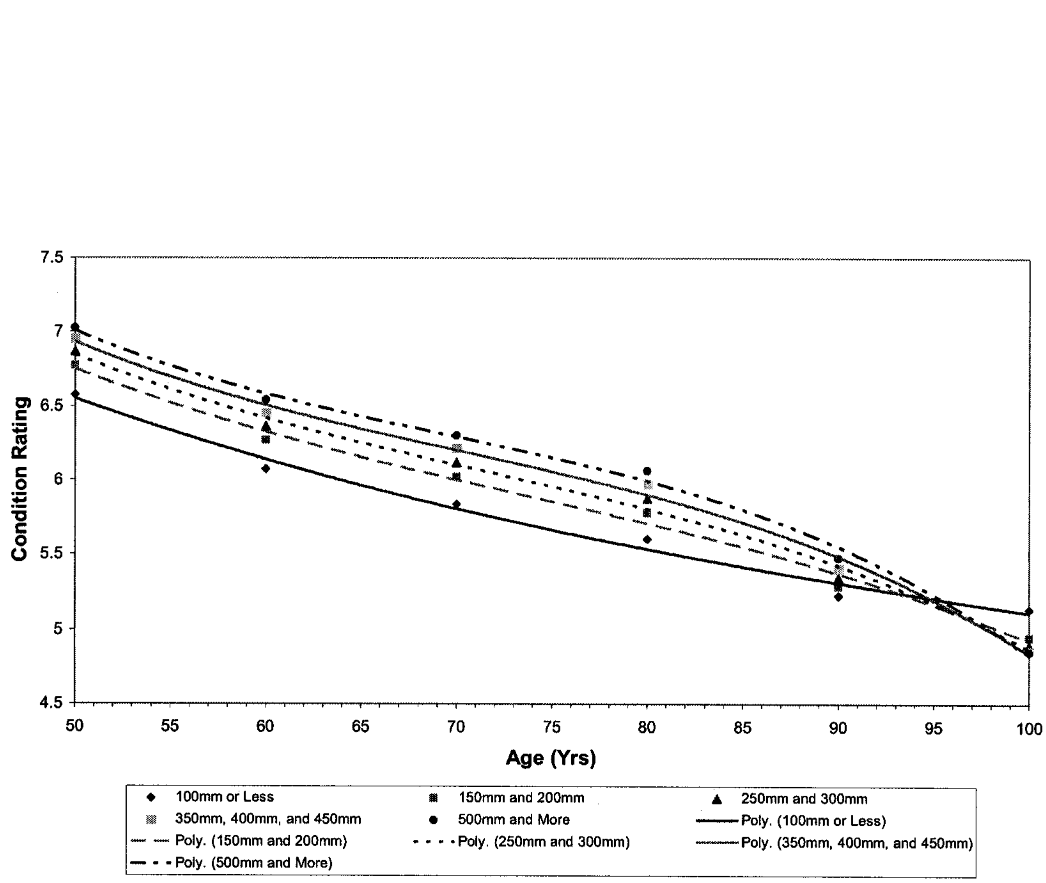


Figure E-97 CI: C-factor (60)-Cathodic Protection (Yes) - Soil Type (Clay) -Breakage Rate (0.1)

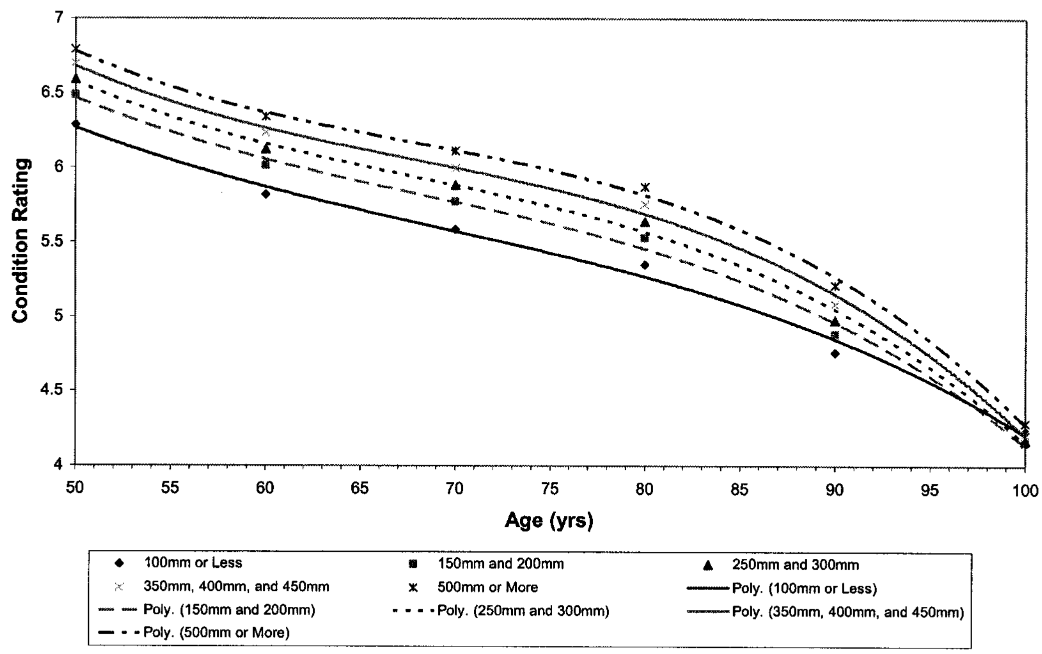


Figure E-98 CI: C-factor (60)-Cathodic Protection (No) - Soil Type (Clay) -Breakage Rate (0.1)

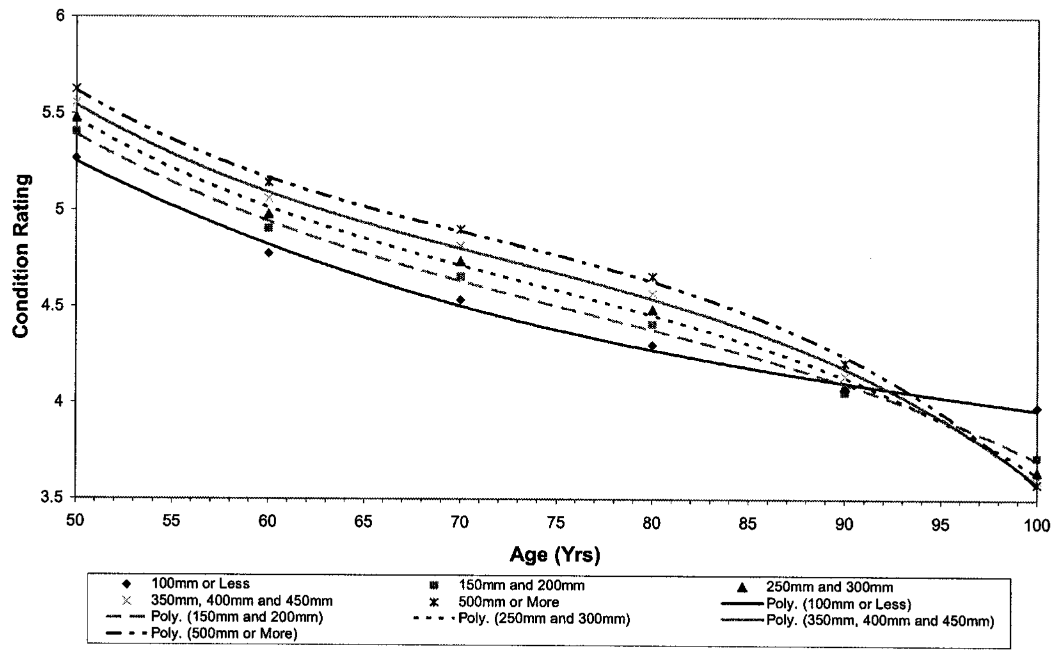


Figure E-99 CI: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

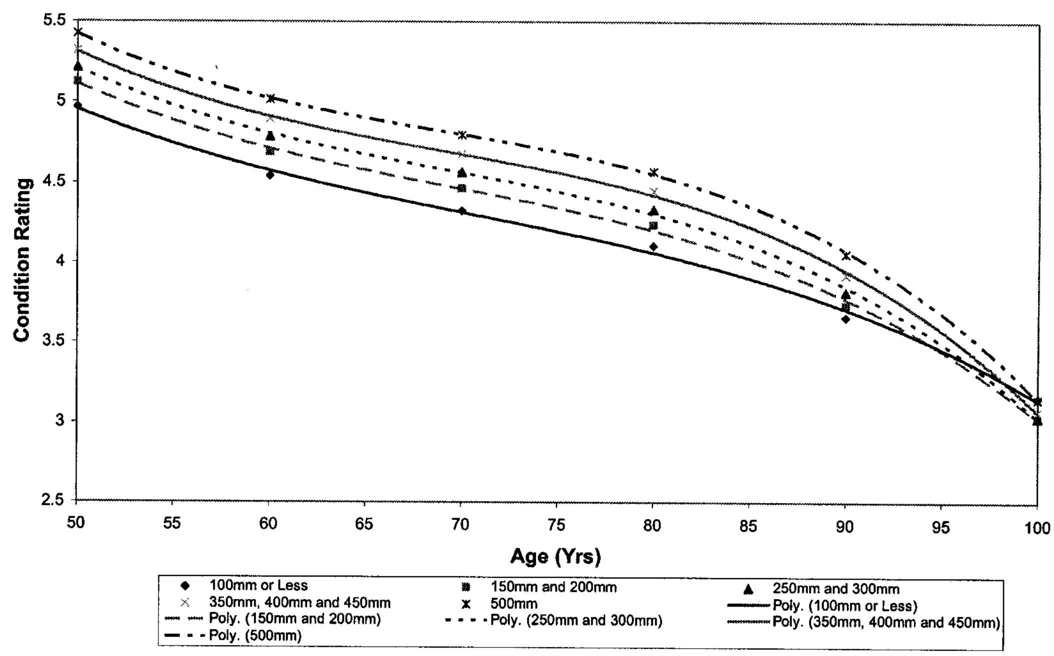


Figure E-100 CI: C-factor (100) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

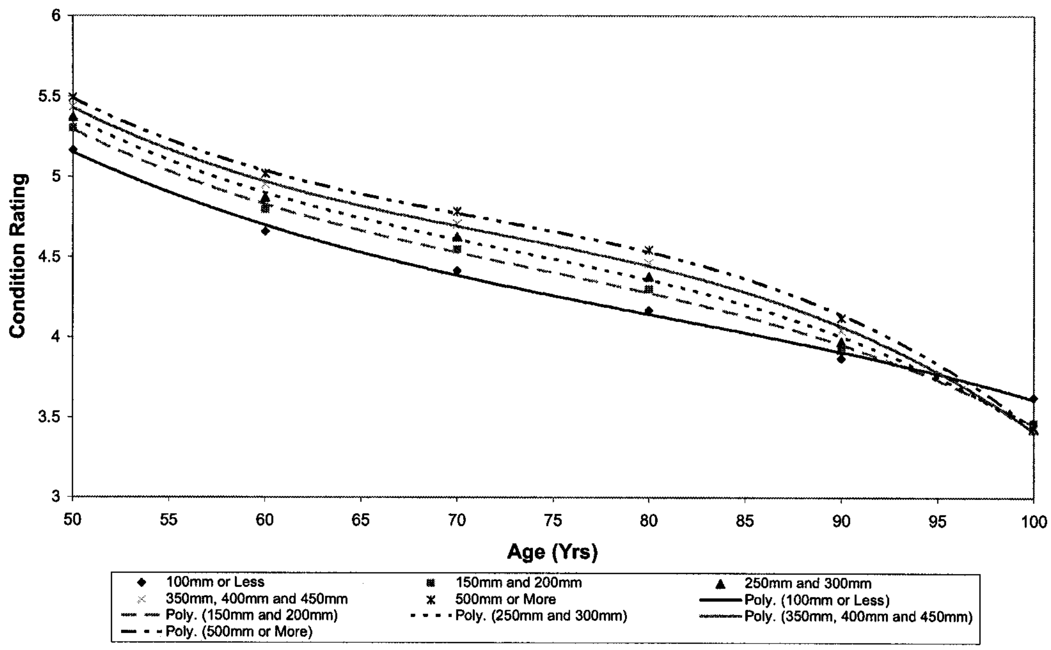


Figure E-101 CI: C-factor (80) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

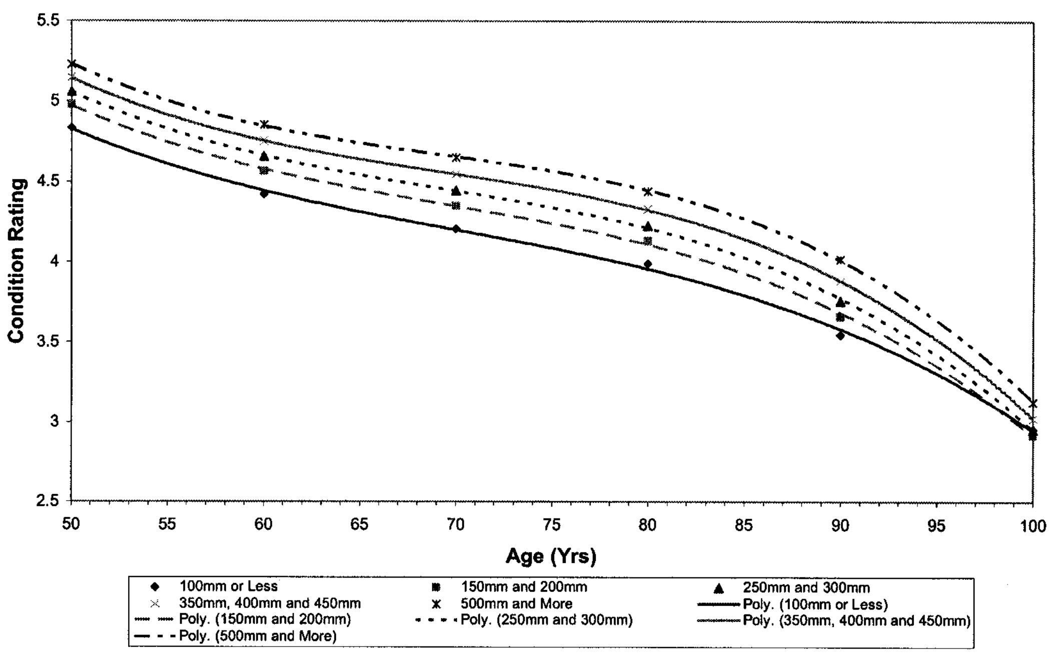


Figure E-102 CI: C-factor (80) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

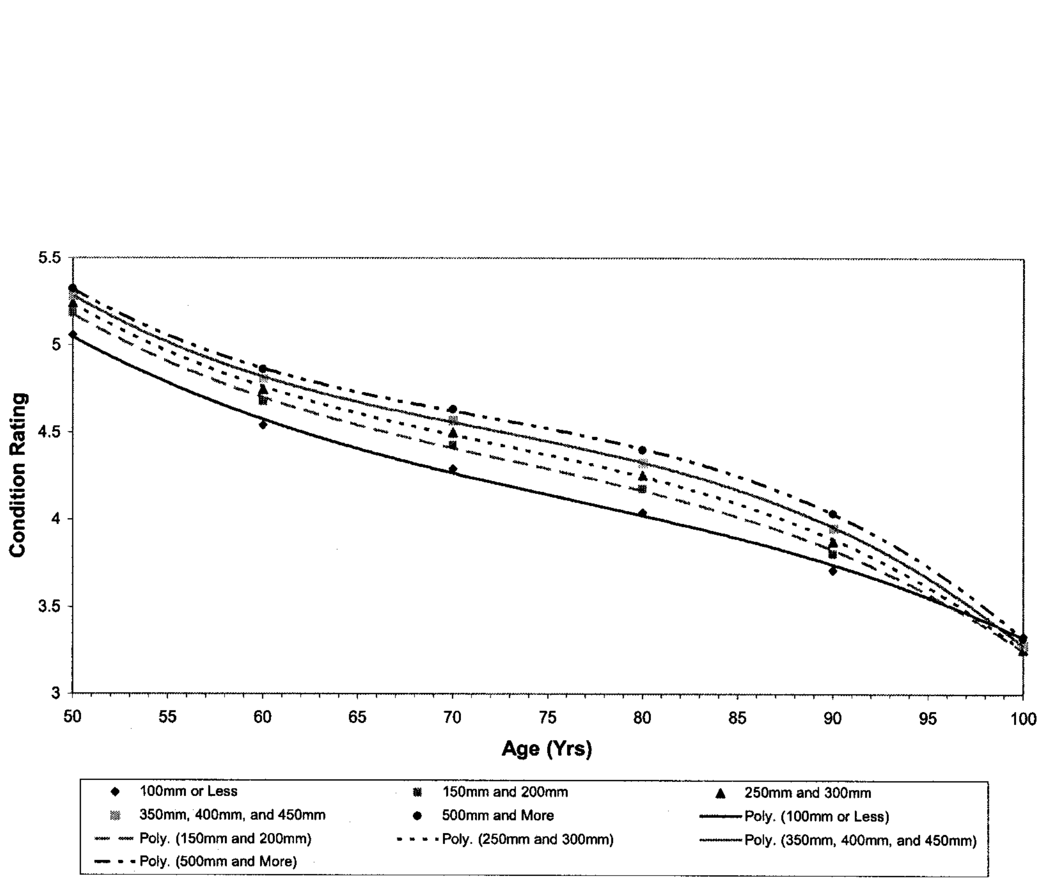


Figure E-103 CI: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

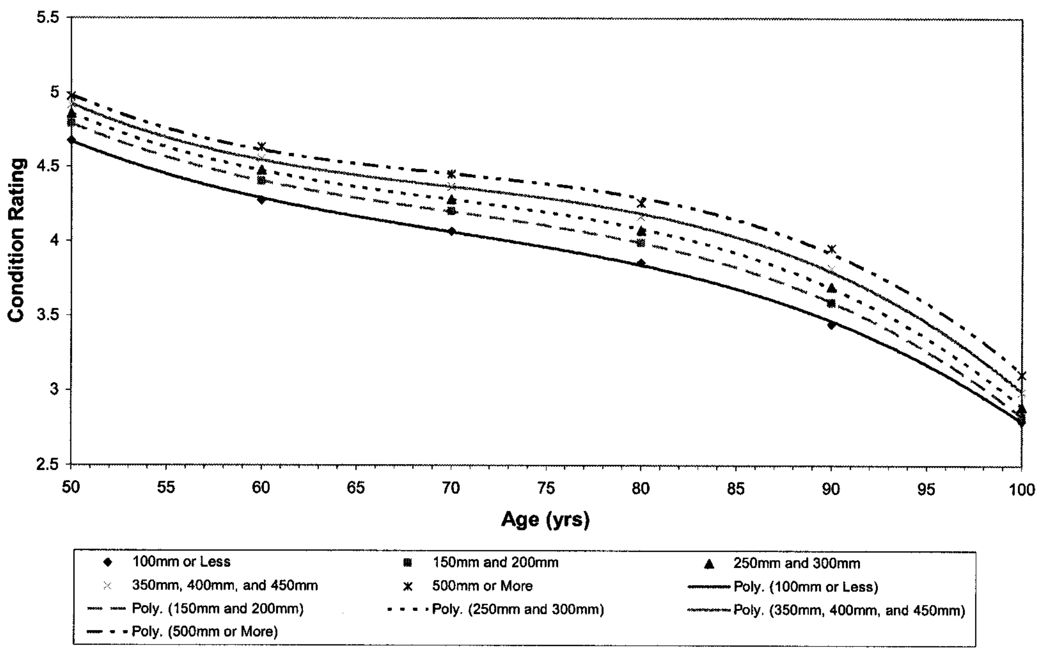


Figure E-104 CI: C-factor (60) - Cathodic Protection (No) - Soil Type (Clay) - Breakage Rate (3)

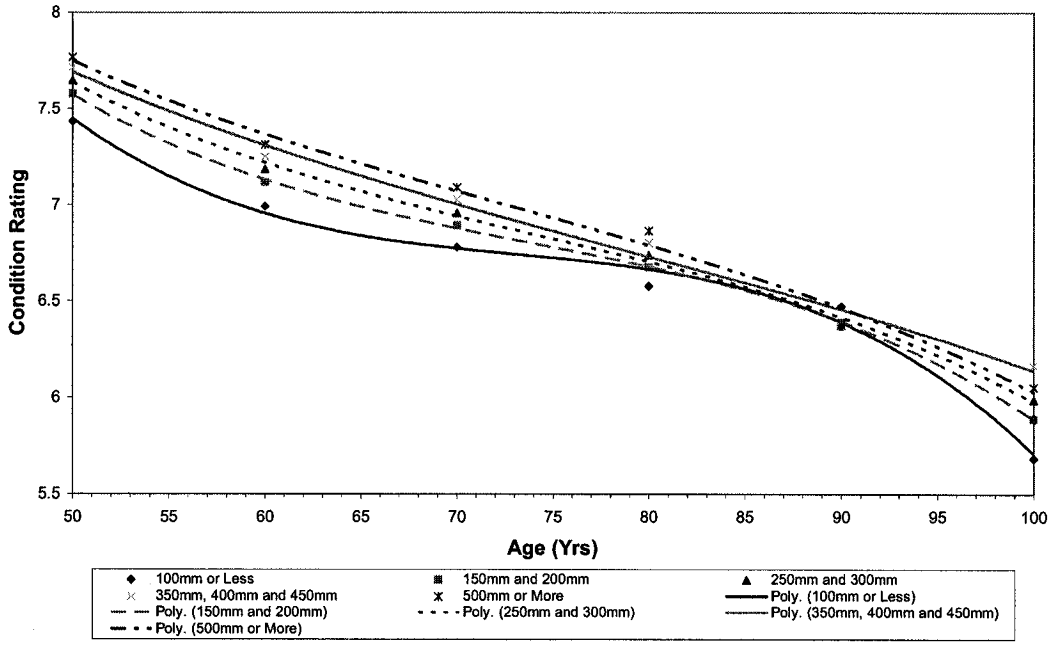


Figure E-105 CI: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Sand)- Breakage Rate (0.1)

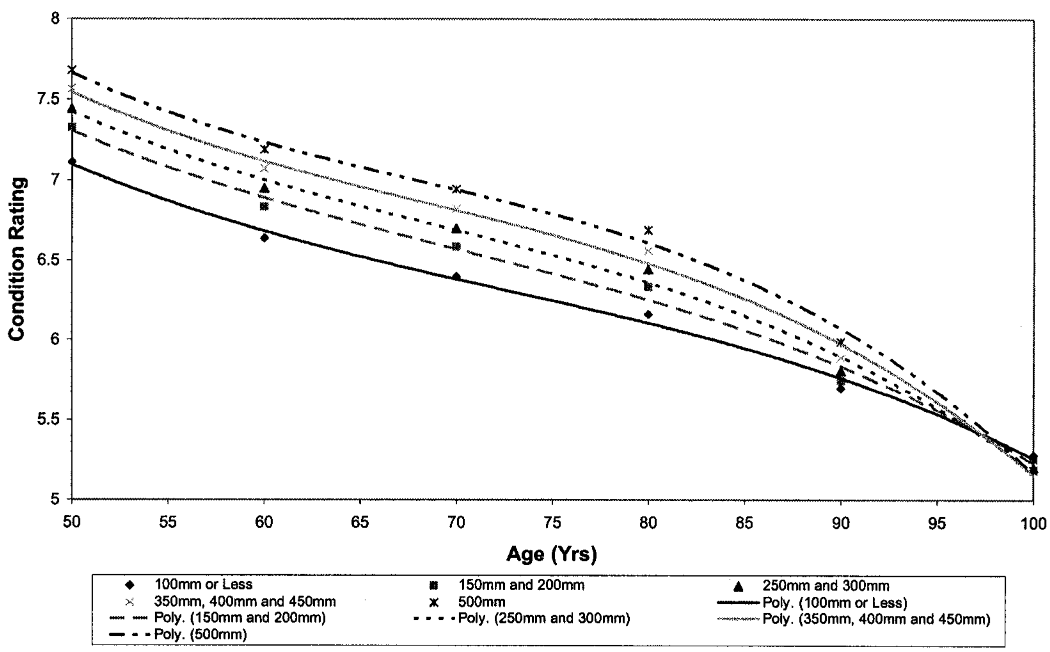


Figure E-106 CI: C-factor (100) - Cathodic Protection (No) - Soil Type (Sand)- Breakage Rate (0.1)

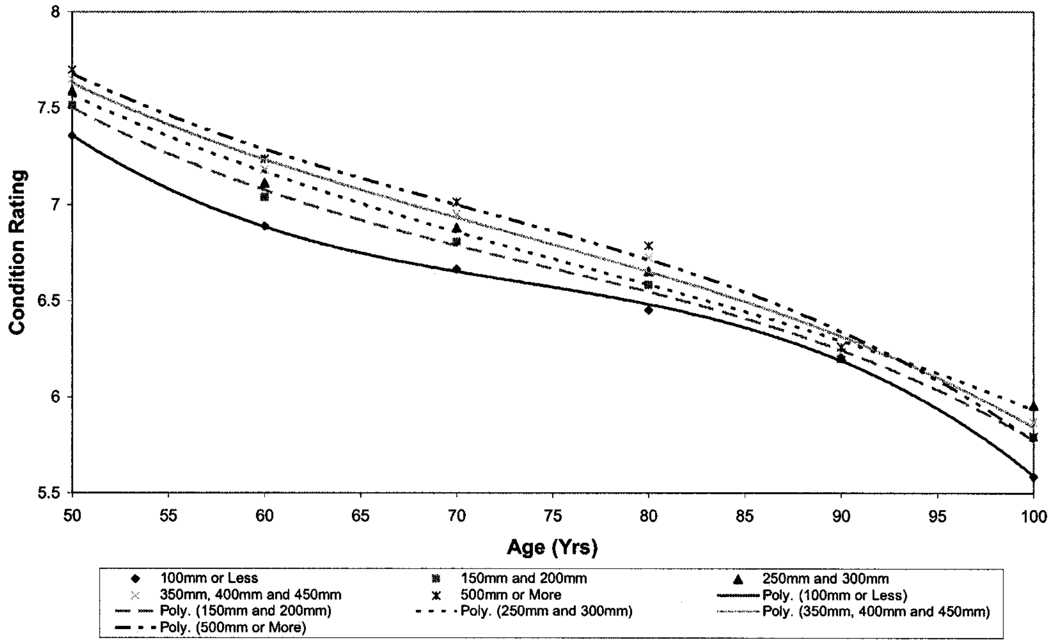


Figure E-107 CI: C-factor (80) - Cathodic Protection (Yes) - Soil Type (Sand)- Breakage Rate (0.1)

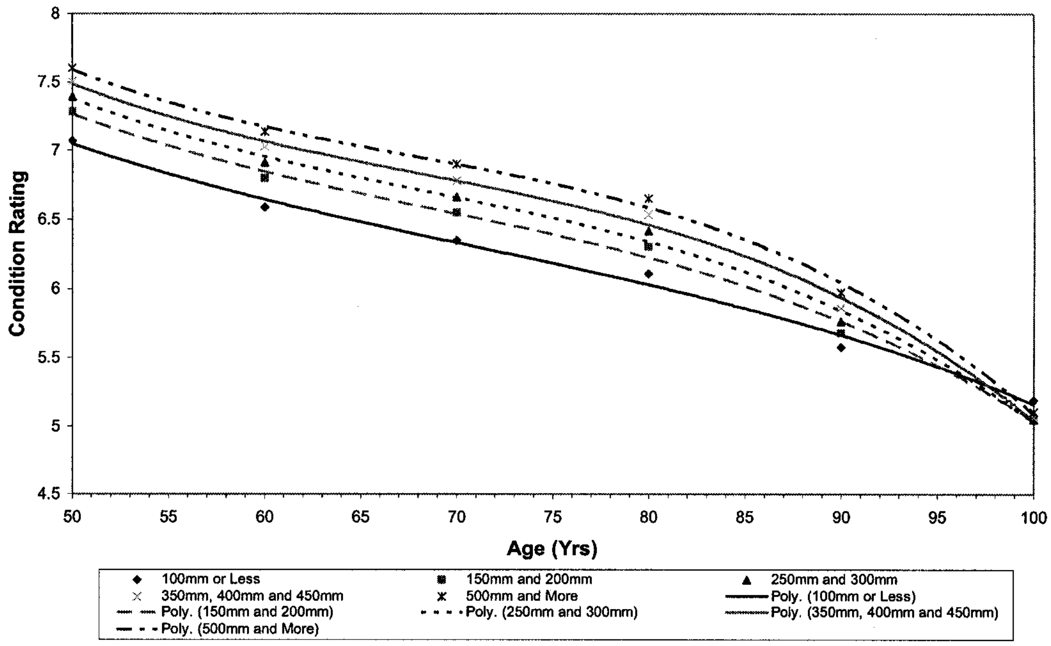


Figure E-108 CI: C-factor (80) - Cathodic Protection (No) - Soil Type (Sand)- Breakage Rate (0.1)

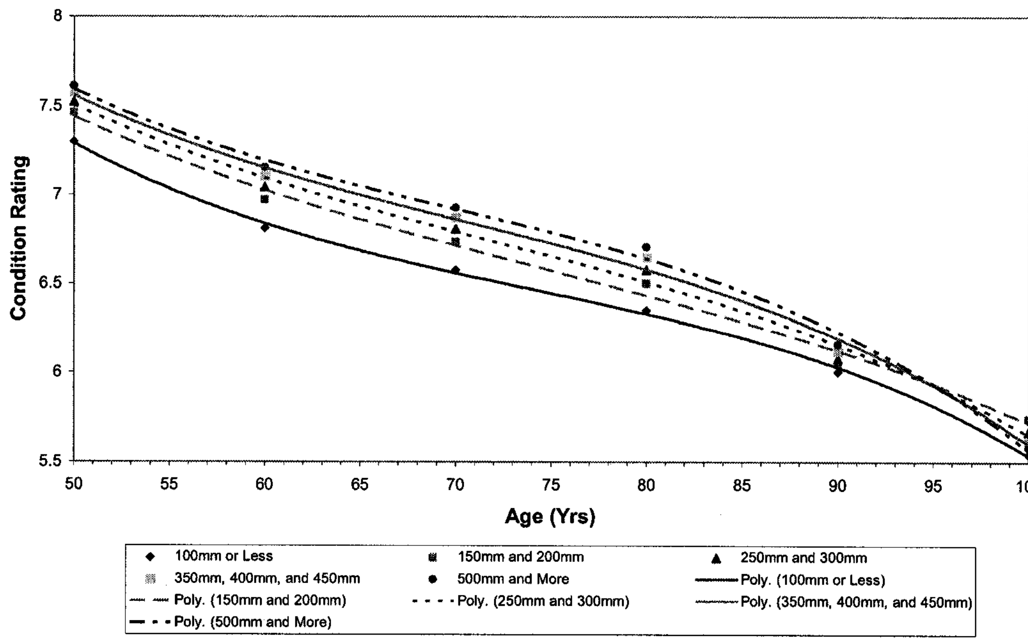


Figure E-109 CI: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Sand)- Breakage Rate (0.1)

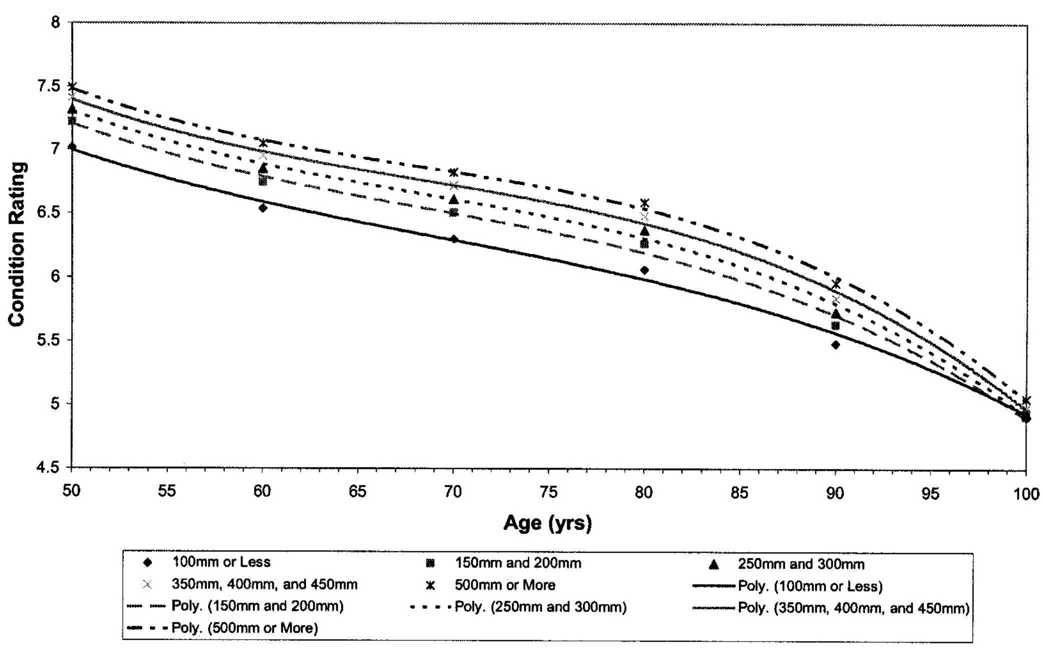


Figure E-110 CI: C-factor (60) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (0.1)

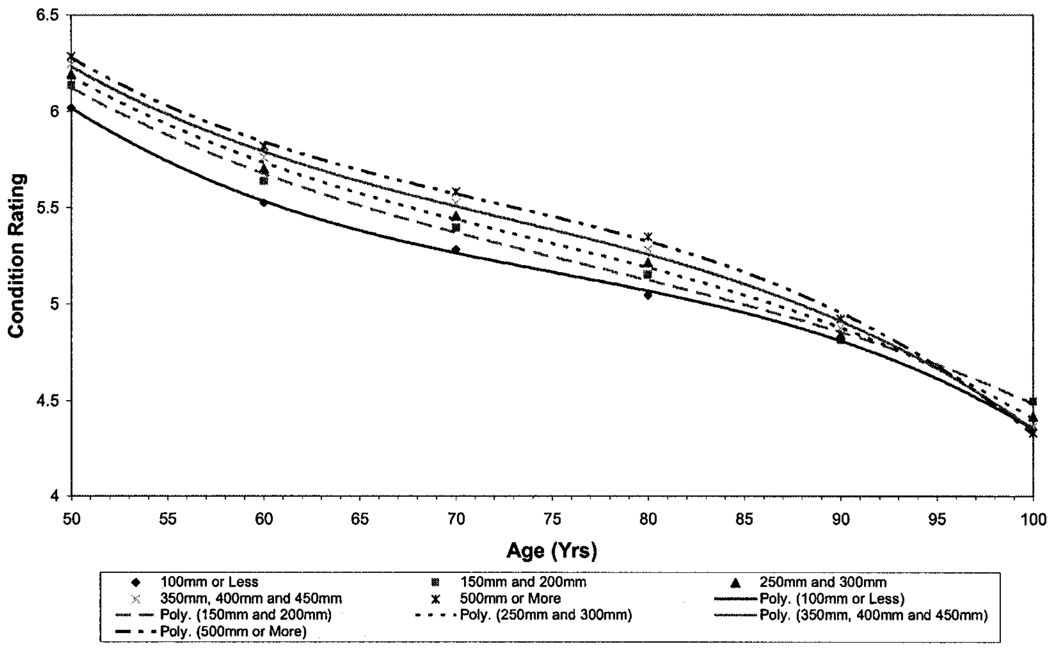


Figure E-111 CI: C-factor (100) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

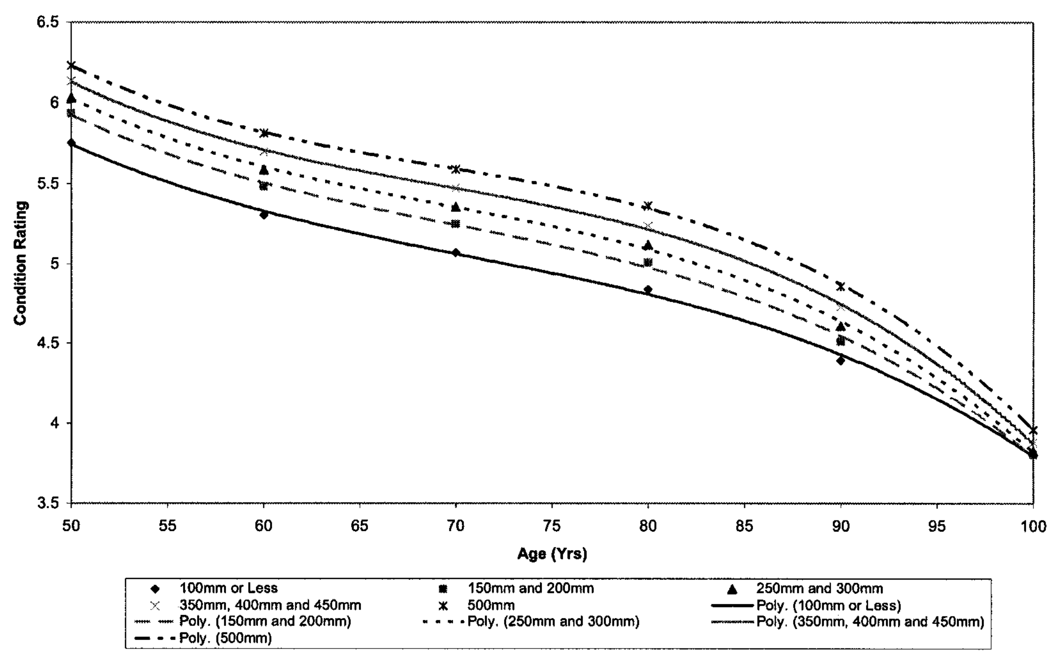


Figure E-112 CI: C-factor (100) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

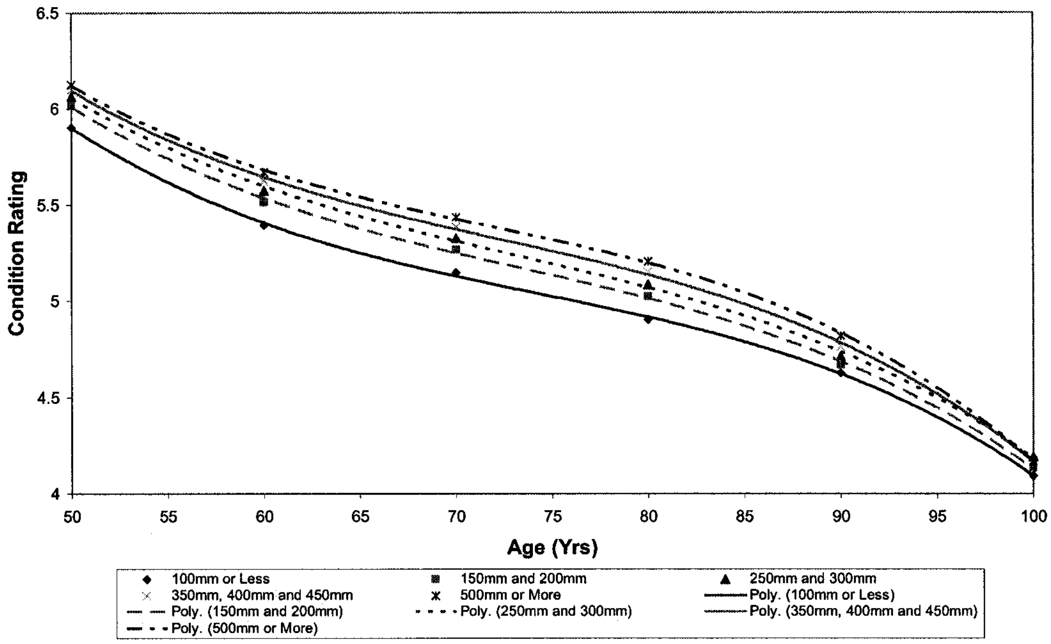


Figure E-113 CI: C-factor (80) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

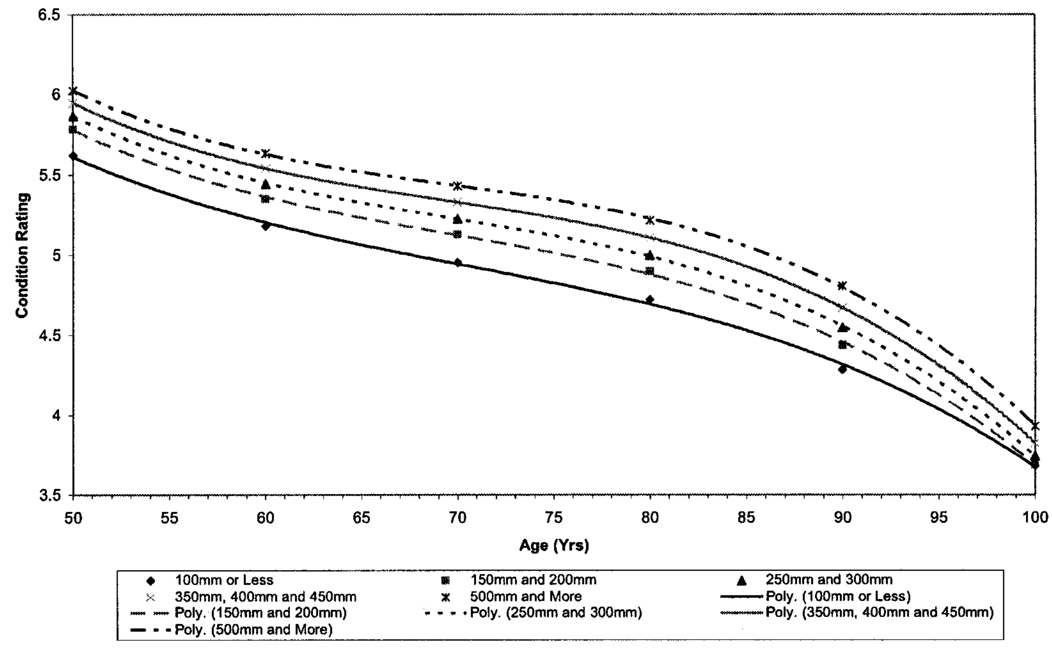


Figure E-114 CI: C-factor (80) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

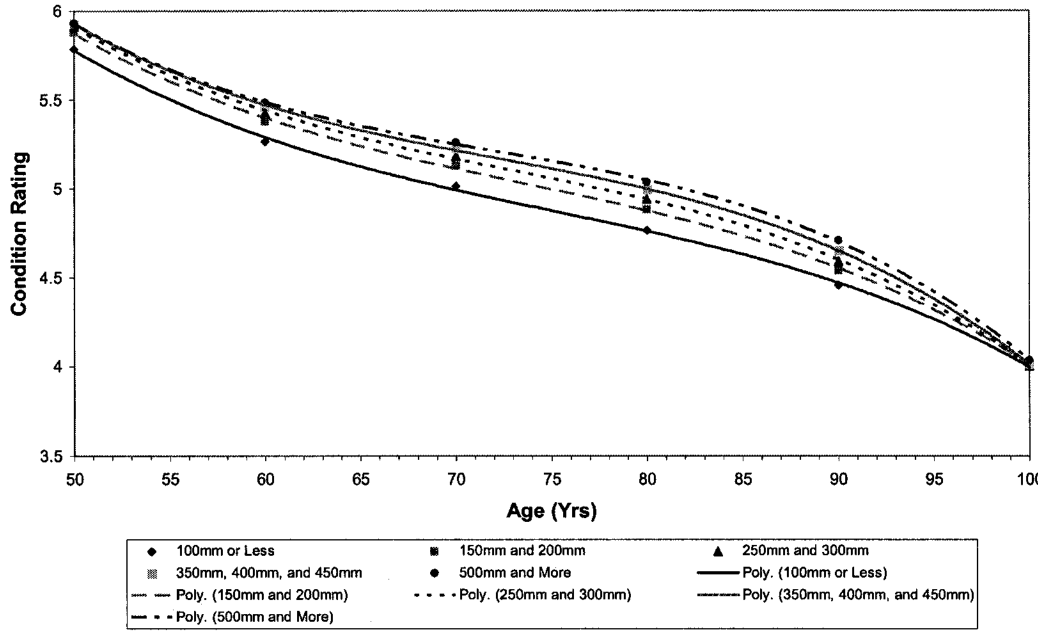


Figure E-115 CI: C-factor (60) - Cathodic Protection (Yes) - Soil Type (Sand) - Breakage Rate (3)

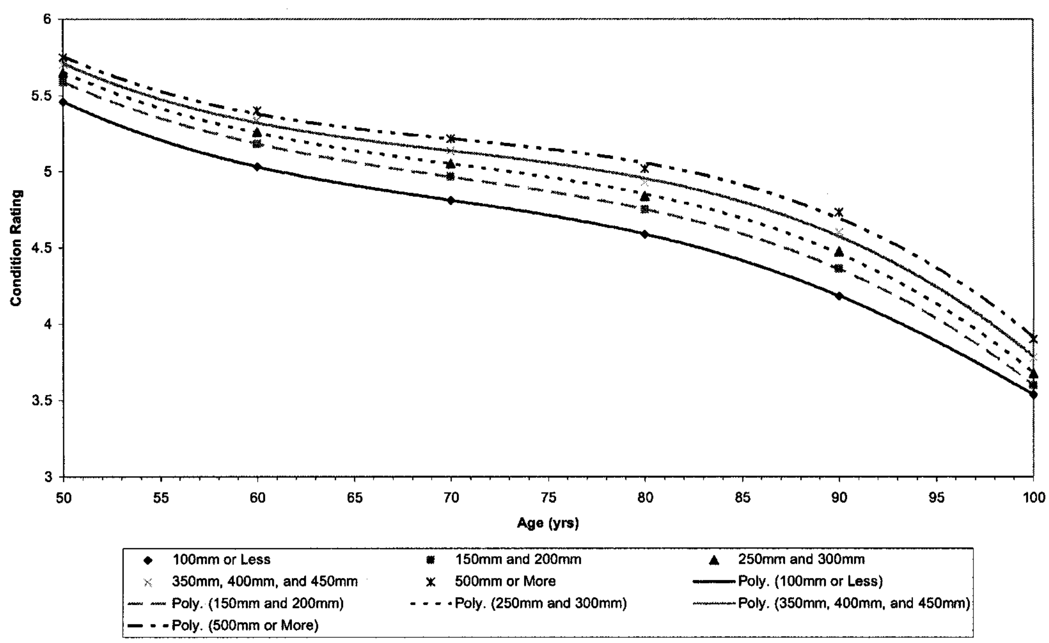


Figure E-116 CI: C-factor (60) - Cathodic Protection (No) - Soil Type (Sand) - Breakage Rate (3)

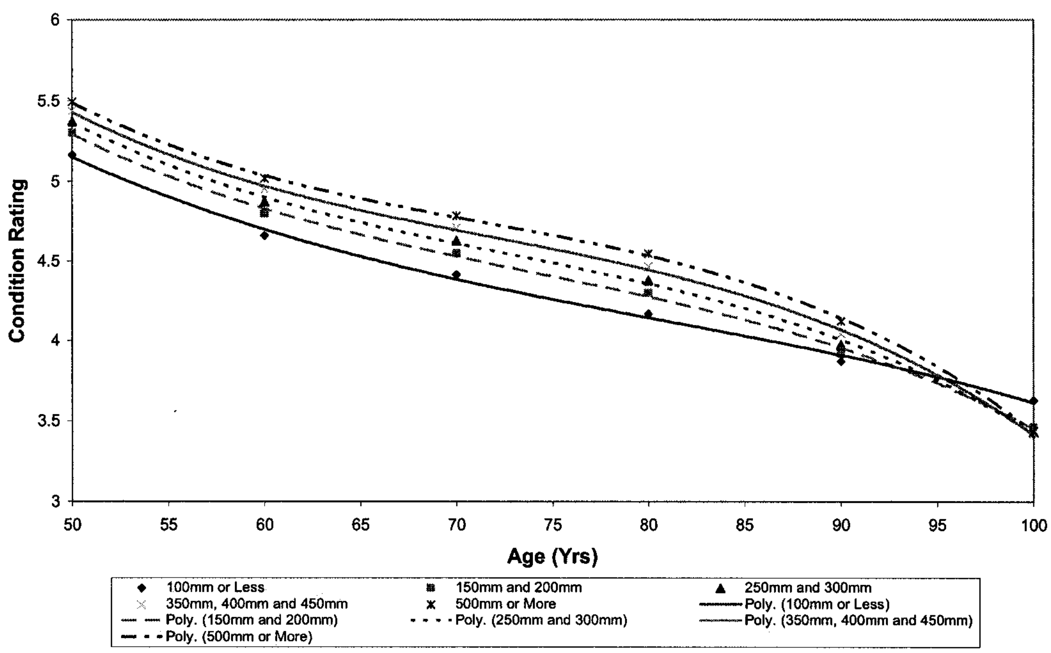


Figure E-117 CI: C-factor (80) - Cathodic Protection (Yes) - Soil Type (Clay) - Breakage Rate (3)

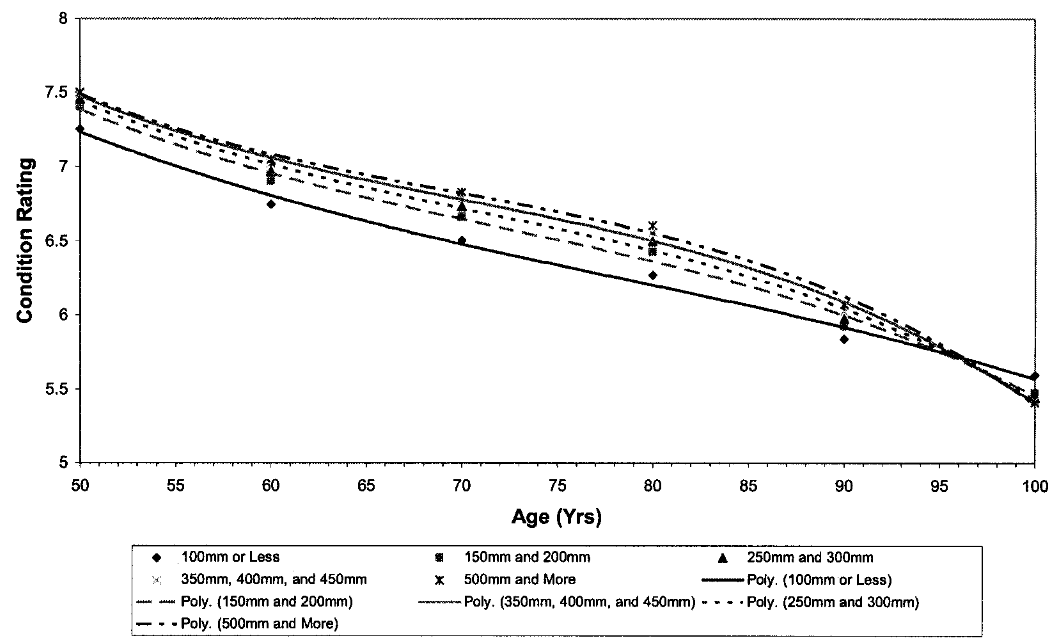


Figure E-118 CI: C-factor (40)- Cathodic Protection (Yes)- Soil Type (Sand)- Breakage Rate (0.1)

APPEDIX (F)

APPENDIX (F)

F. CR-Predictor AHP APPLICATION

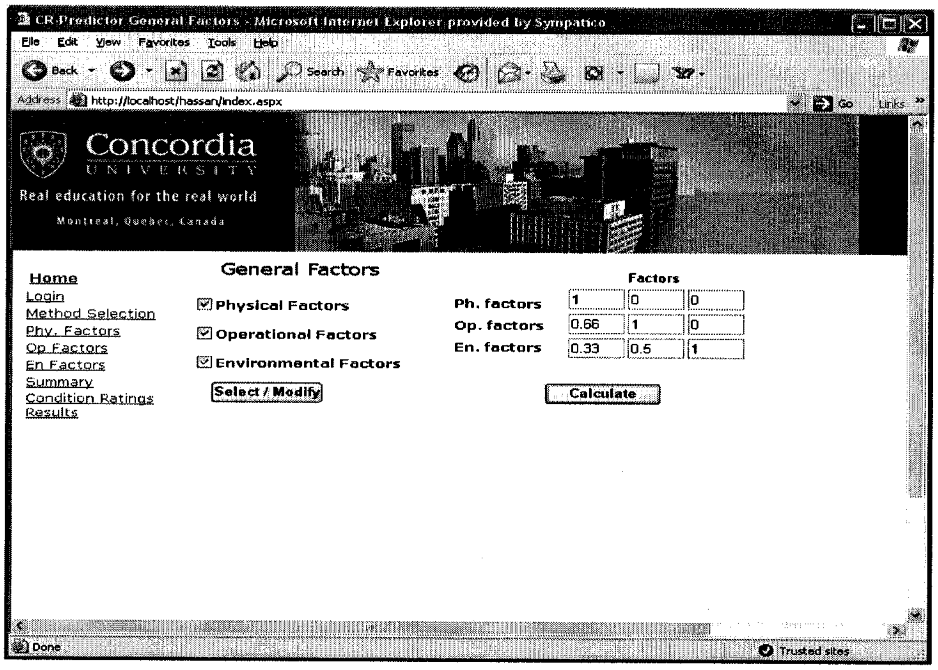


Figure F-1 General Factors Selection

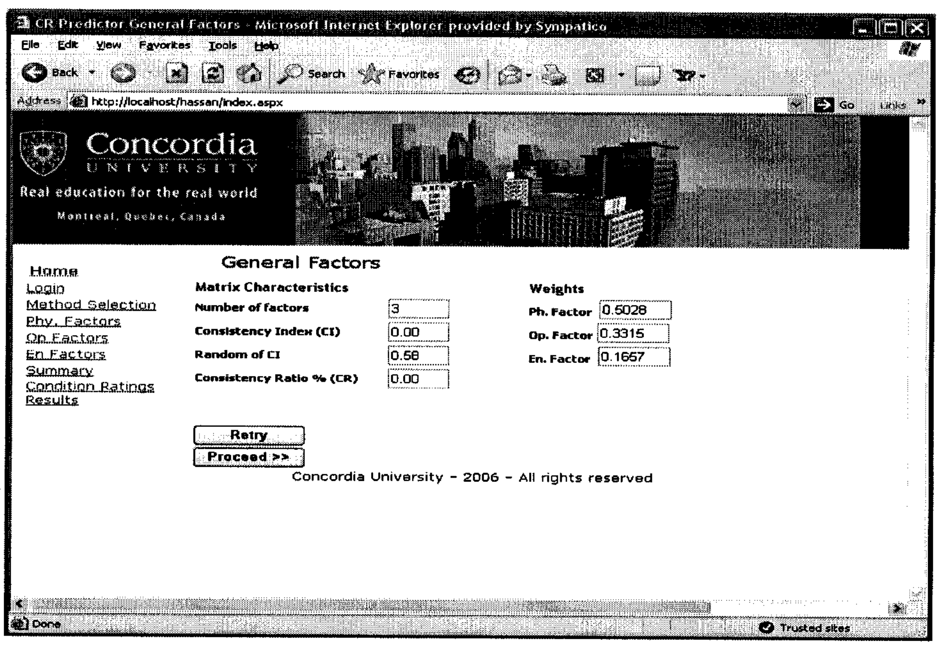


Figure F-2 General Factors Importance Weights

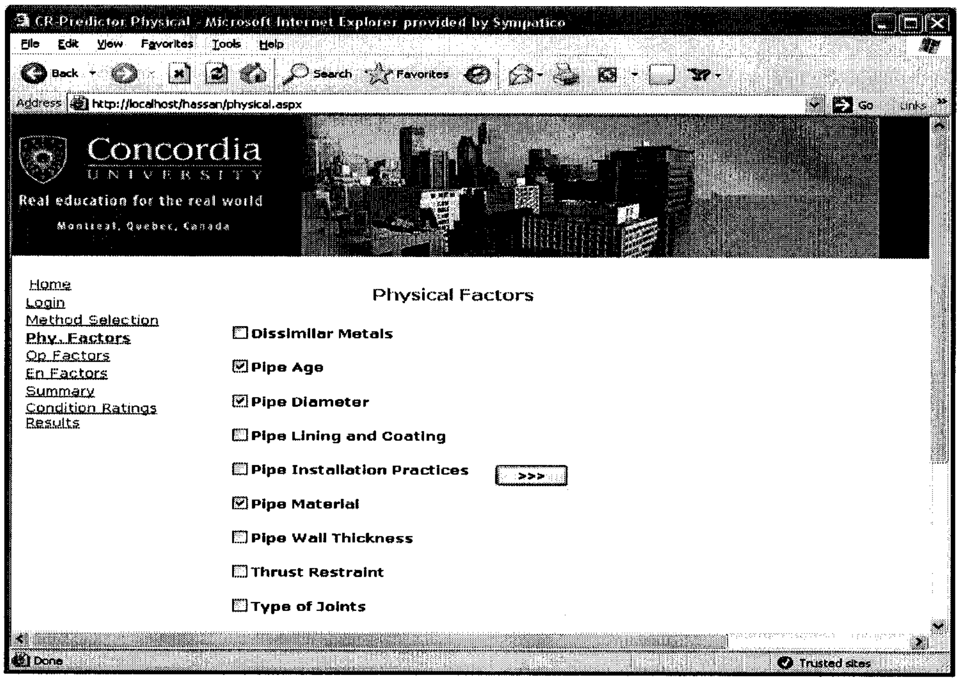


Figure F-3 Physical Factors Selection

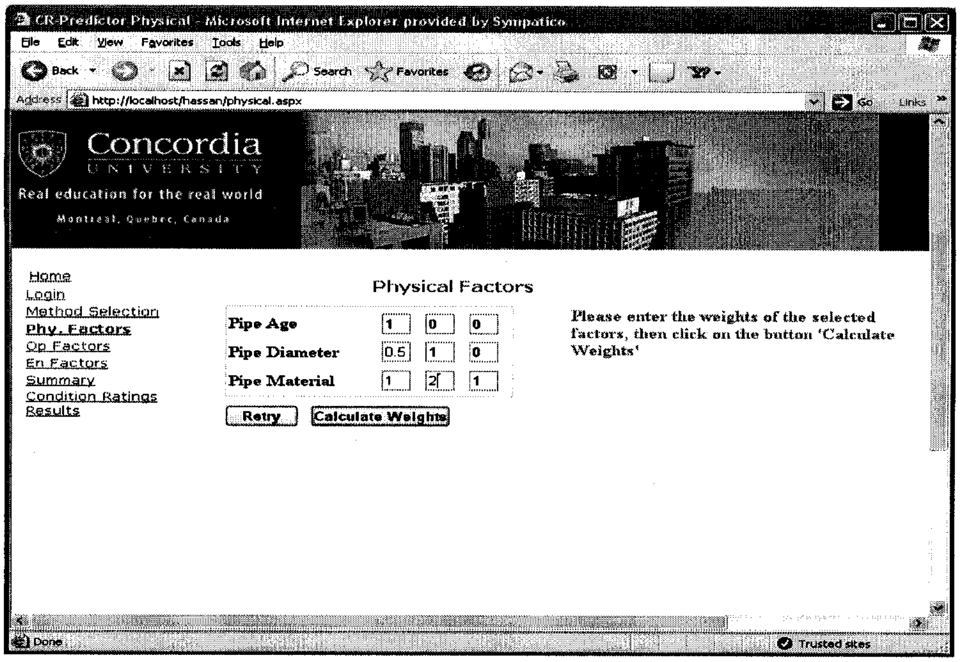


Figure F-4 Assigning Physical Factors Importance Values

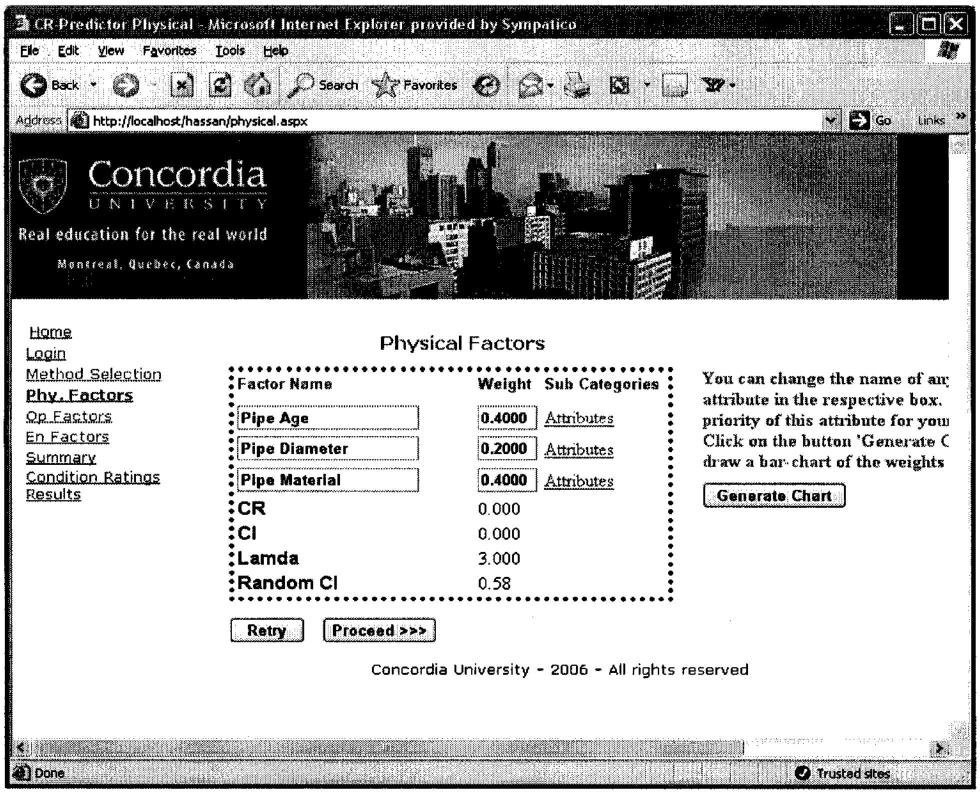


Figure F-5 Physical Factors Importance Weights

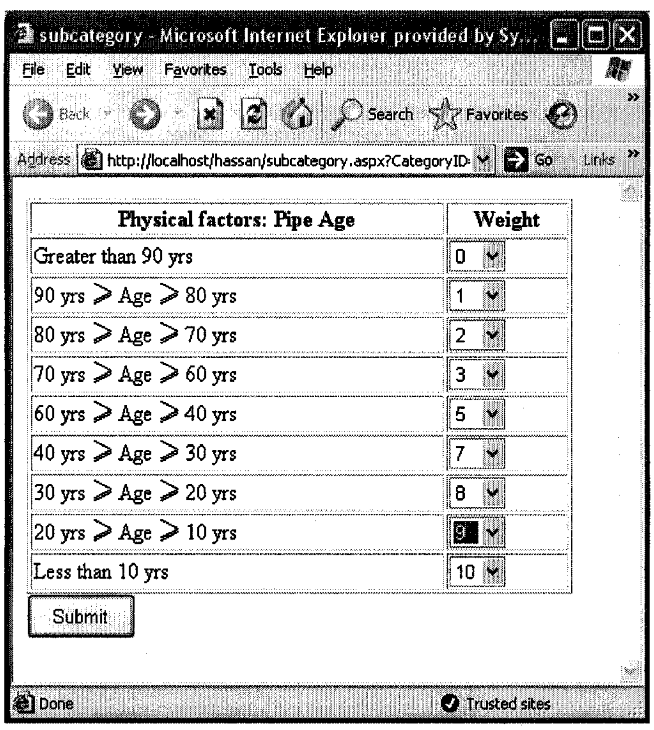


Figure F-6 Pipe Age Attributes Effect Values

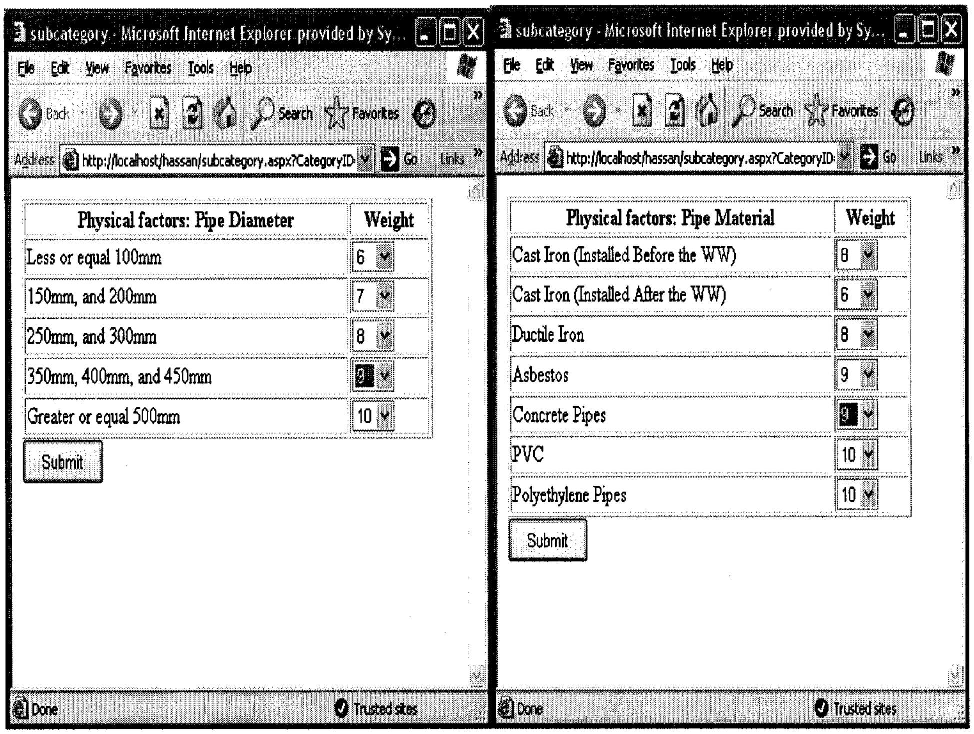


Figure F-7 Pipe Diameter and Pipe Material Attributes Effect Values

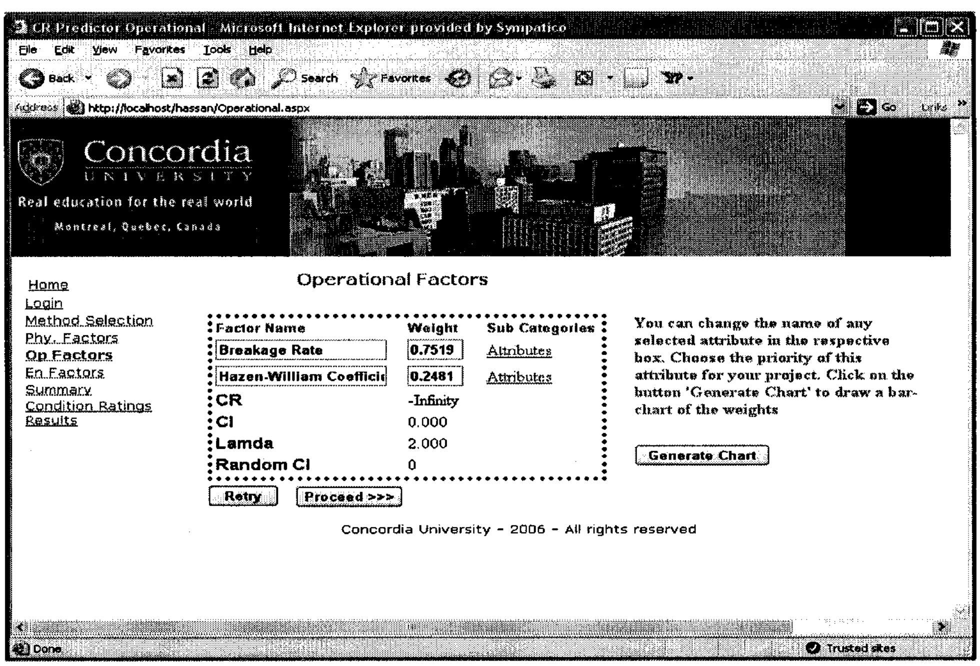


Figure F-8 Operational Sub-factors Importance Weights

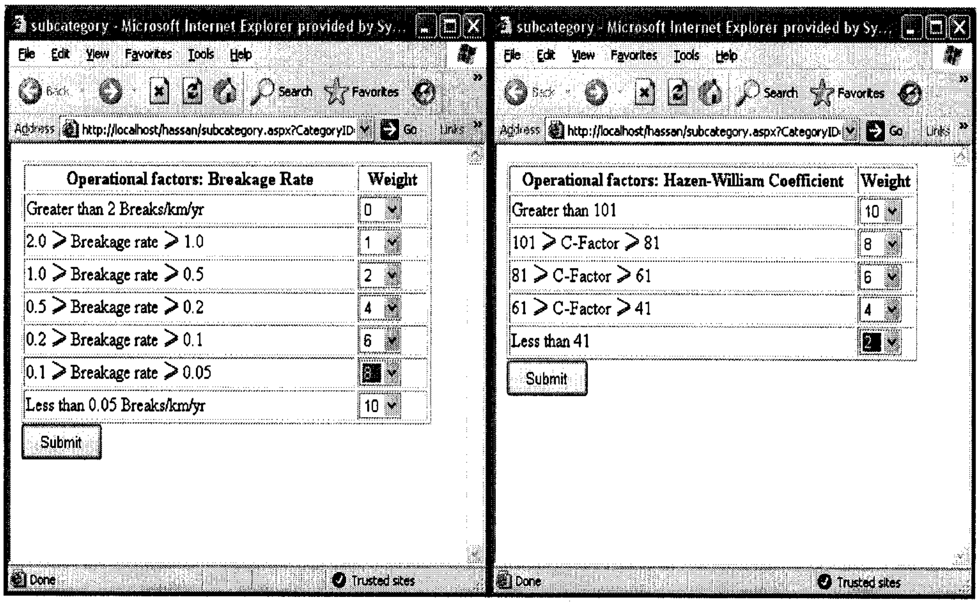


Figure F-9 Breakage Rate and C-Factor Attributes Effect Values

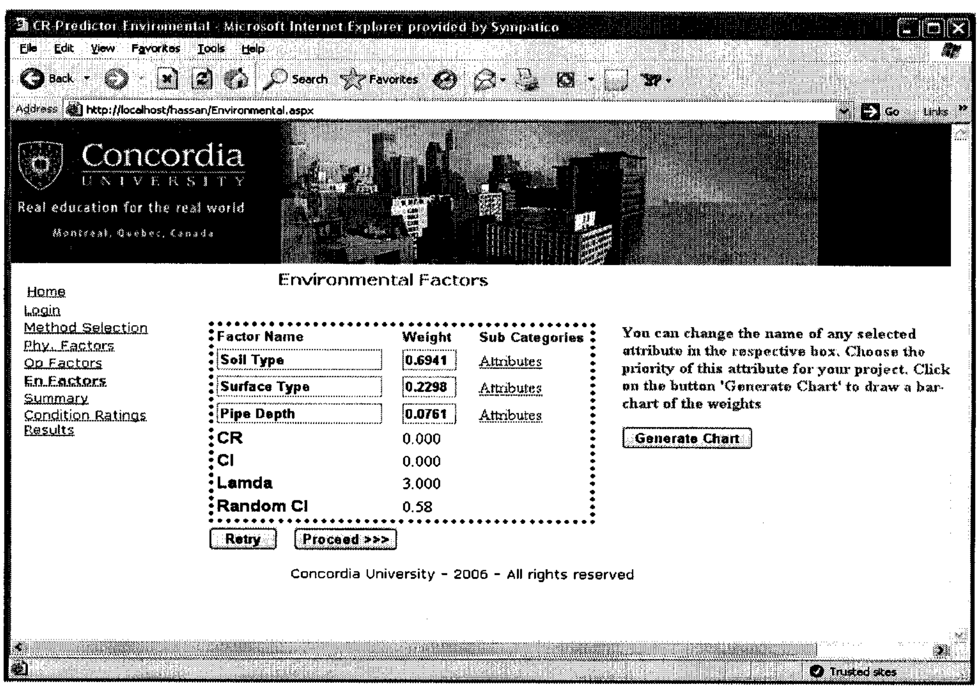


Figure F-10 Environmental Sub-factors Importance Weights

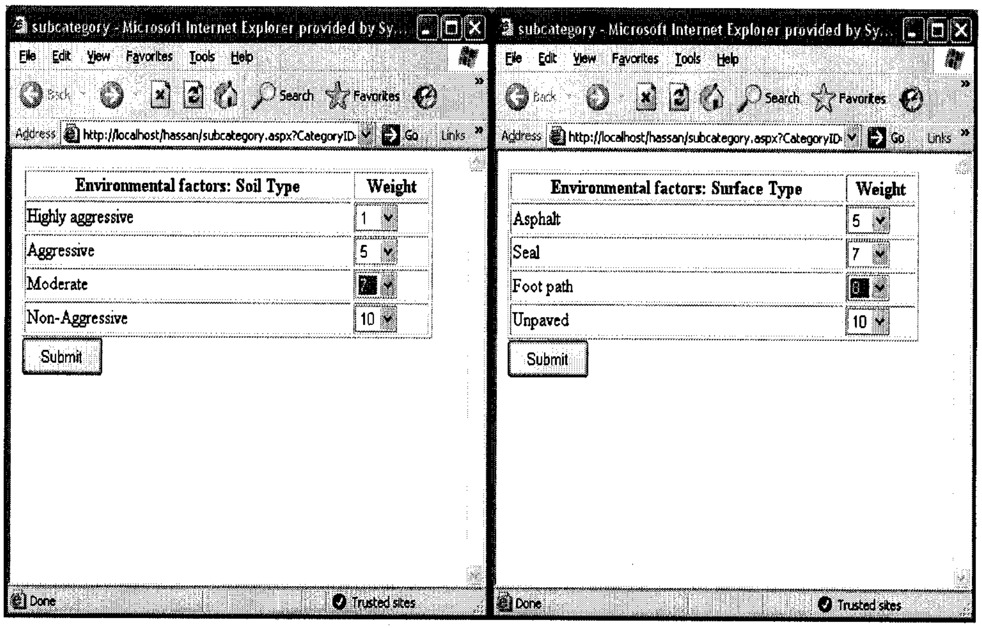


Figure F-11 Soil Type and Surface Type Attributes Effect Values

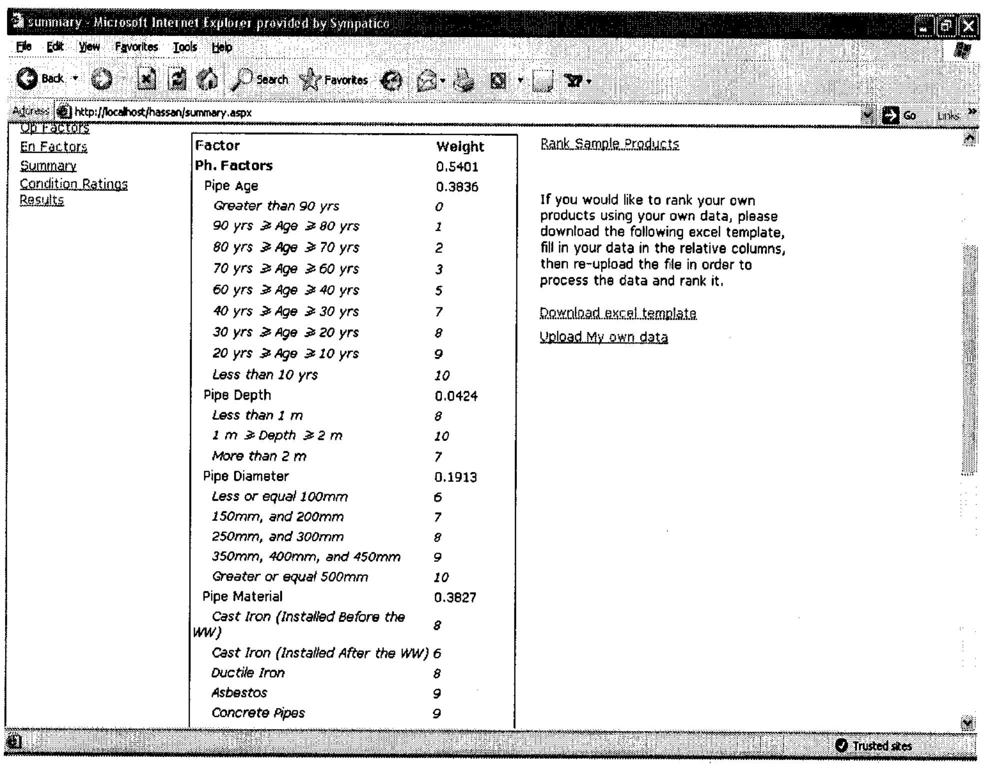
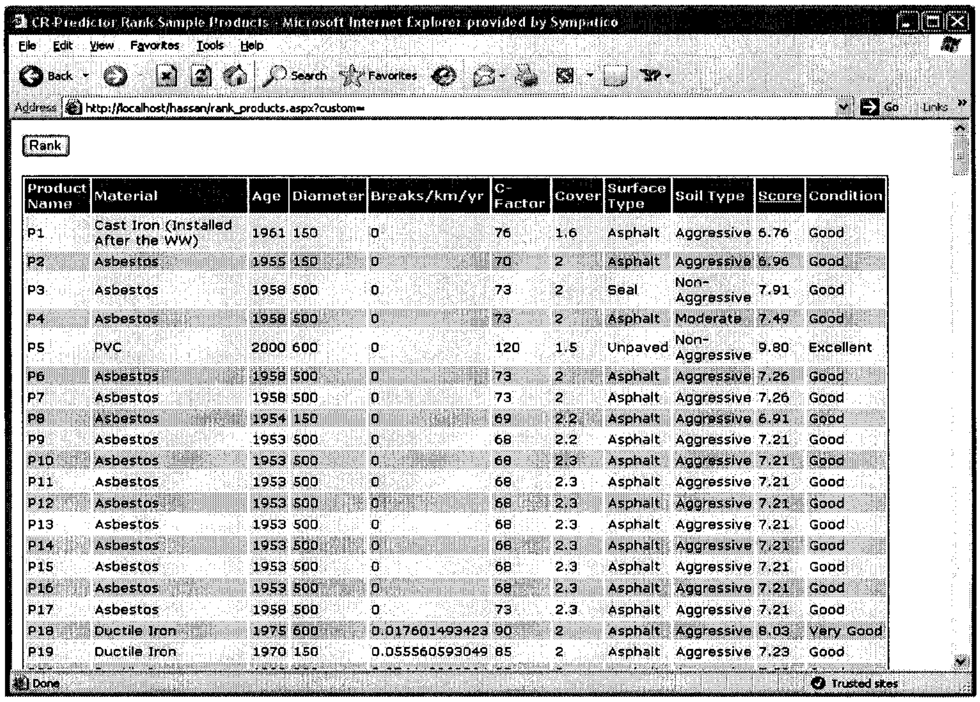


Figure F-12 Results Summary



Product Name	Material	Age	Diameter	Breaks/km/yr	C-Factor	Cover	Surface Type	Soil Type	Score	Condition
P1	Cast Iron (Installed After the WW)	1961	150	0	76	1.6	Asphalt	Aggressive	6.76	Good
P2	Asbestos	1955	150	0	70	2	Asphalt	Aggressive	6.96	Good
P3	Asbestos	1958	500	0	73	2	Seal	Non-Aggressive	7.91	Good
P4	Asbestos	1958	500	0	73	2	Asphalt	Moderate	7.49	Good
P5	PVC	2000	600	0	120	1.5	Unpaved	Non-Aggressive	9.80	Excellent
P6	Asbestos	1958	500	0	73	2	Asphalt	Aggressive	7.26	Good
P7	Asbestos	1958	500	0	73	2	Asphalt	Aggressive	7.26	Good
P8	Asbestos	1954	150	0	69	2.2	Asphalt	Aggressive	6.91	Good
P9	Asbestos	1953	500	0	68	2.2	Asphalt	Aggressive	7.21	Good
P10	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P11	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P12	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P13	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P14	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P15	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P16	Asbestos	1953	500	0	68	2.3	Asphalt	Aggressive	7.21	Good
P17	Asbestos	1958	500	0	73	2.3	Asphalt	Aggressive	7.21	Good
P18	Ductile Iron	1975	600	0.017601493423	90	2	Asphalt	Aggressive	8.03	Very Good
P19	Ductile Iron	1970	150	0.055560593049	85	2	Asphalt	Aggressive	7.23	Good

Figure F-13 Condition Assessment Results